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[2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import re
import time
import warnings
import sqlite3
from sqlalchemy import create_engine # database connection
import csv
import os
warnings.filterwarnings("ignore")
import datetime as dt
import numpy as np
from nltk.corpus import stopwords
from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import normalize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.manifold import TSNE
import seaborn as sns
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics.classification import accuracy_score, log_loss
from sklearn.feature_extraction.text import TfidfVectorizer
from collections import Counter
from scipy.sparse import hstack
from sklearn.multiclass import OneVsRestClassifier
from sklearn.svm import SVC
from sklearn.model_selection import StratifiedKFold
from collections import Counter, defaultdict
from sklearn.calibration import CalibratedClassifierCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
import math
from sklearn.metrics import normalized_mutual_info_score
from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import SGDClassifier
from mlxtend.classifier import StackingClassifier

from sklearn import model_selection
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_recall_curve, auc, roc_curve
```

4. Machine Learning Models

4.1 Reading data from file and storing into sql table

[2]:
```
#Creating db file from csv
if not os.path.isfile('train.db'):
    disk_engine = create_engine('sqlite:///train.db')
    start = dt.datetime.now()
    chunksize = 180000
    j = 0
    index_start = 1
#     for df in pd.read_csv('final_features.csv', names=['Unnamed: 0','id','is_duplicate','cwc
    for df in pd.read_csv('final_features.csv', names=['Unnamed:␣
↪0','id','is_duplicate','cwc_min','cwc_max','csc_min','csc_max','ctc_min','ctc_max','last_wo
↪chunksize=chunksize, iterator=True, encoding='utf-8', ):
        df.index += index_start
        j+=1
        print('{} rows'.format(j*chunksize))
        df.to_sql('data', disk_engine, if_exists='append')
        index_start = df.index[-1] + 1
```

```
180000 rows
360000 rows
540000 rows
```

[3]:
```
#http://www.sqlitetutorial.net/sqlite-python/create-tables/
def create_connection(db_file):
    """ create a database connection to the SQLite database
        specified by db_file
    :param db_file: database file
    :return: Connection object or None
    """
    try:
        conn = sqlite3.connect(db_file)
        return conn
    except Error as e:
        print(e)
```

```
    return None


def checkTableExists(dbcon):
    cursr = dbcon.cursor()
    str = "select name from sqlite_master where type='table'"
    table_names = cursr.execute(str)
    print("Tables in the databse:")
    tables =table_names.fetchall()
    print(tables[0][0])
    return(len(tables))
```

[4]:
```
read_db = 'train.db'
conn_r = create_connection(read_db)
checkTableExists(conn_r)
conn_r.close()
```

```
Tables in the databse:
data
```

[5]:
```
# try to sample data according to the computing power you have
if os.path.isfile(read_db):
    conn_r = create_connection(read_db)
    if conn_r is not None:
        # for selecting first 1M rows
        # data = pd.read_sql_query("""SELECT * FROM data LIMIT 100001;""",␣
 ↪conn_r)

        # for selecting random points
        data = pd.read_sql_query("SELECT * From data ORDER BY RANDOM() LIMIT␣
 ↪100001;", conn_r)
        conn_r.commit()
        conn_r.close()
```

[6]:
```
# remove the first row
data.drop(data.index[0], inplace=True)
y_true = data['is_duplicate']
data.drop(['Unnamed: 0', 'id','index','is_duplicate'], axis=1, inplace=True)
```

[7]:
```
data.head()
```

[7]:

	cwc_min	cwc_max	csc_min	csc_max	\
1	0.199996000079998	0.111109876556927	0.799984000319994	0.22222098766118	
2	0.0	0.0	0.399992000159997	0.249996875039062	
3	0.999975000624984	0.666655555740738	0.999975000624984	0.444439506227709	
4	0.249993750156246	0.199996000079998	0.66664444518516	0.285710204139941	
5	0.749981250468738	0.599988000239995	0.0	0.0	

```
              ctc_min             ctc_max last_word_eq first_word_eq  \
1  0.454541322351615   0.15151469237972          0.0           0.0
2  0.249996875039062    0.0999995000025          0.0           0.0
3  0.799992000079999  0.444441975322359          0.0           1.0
4  0.374995312558593  0.249997916684028          0.0           1.0
5  0.599988000239995  0.374995312558593          0.0           0.0

  abs_len_diff mean_len  ...              290_y              291_y  \
1         22.0     22.0  ...   -40.797933138907   8.97839166130871
2         12.0     14.0  ...  -5.10840830206871  -12.7033559828997
3          8.0     14.0  ...  -8.16833129525185  -7.98917800188065
4          4.0     10.0  ...   -3.5118428170681    9.3120232373476
5          3.0      6.5  ...  -3.97895254939795   9.72298616170883

               292_y              293_y              294_y              295_y  \
1  -8.08087987091858  -5.95069866674021     21.62886095047   3.83761356770992
2   3.01767840236425  -5.51216715574264    -1.6194202452898   3.46952717006207
3    -6.4671797528863  -1.74959287047386  0.744230836629868   4.27597142755985
4   11.2907861545682  -4.91546251252294  -9.53268766403198   5.91840241849422
5   6.70482552051544   2.72654302418232   8.79498007893562  -9.00952172279358

               296_y              297_y              298_y  \
1  -20.3113829344511   -3.94237789511681   32.9755200780928
2  -16.5749972909689    3.01555845141411  -2.97053062915802
3   5.14116267859936   -6.29830634593964  0.734777197241783
4   18.6559449359775  -0.233358412981033  -2.37264208495617
5  -16.9633708233014   -2.12013705074787  -6.94663305580616

               299_y
1    6.6558423275128
2   9.47112828493118
3  -10.2557970052585
4  -0.541556566953659
5    5.1492529809475

[5 rows x 626 columns]
```

4.2 Converting strings to numerics

[8]:
```python
# after we read from sql table each entry was read it as a string
# we convert all the features into numeric before we apply any model
cols = list(data.columns)
for i in cols:
    data[i] = data[i].apply(pd.to_numeric)
    print(i)
```

```
cwc_min
cwc_max
csc_min
```

csc_max
ctc_min
ctc_max
last_word_eq
first_word_eq
abs_len_diff
mean_len
token_set_ratio
token_sort_ratio
fuzz_ratio
fuzz_partial_ratio
longest_substr_ratio
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freq_qid2
q1len
q2len
q1_n_words
q2_n_words
word_Common
word_Total
word_share
freq_q1+q2
freq_q1-q2
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2_x
3_x
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```

[9]:
```
# https://stackoverflow.com/questions/7368789/
↪convert-all-strings-in-a-list-to-int
y_true = list(map(int, y_true.values))
```

[16]:
```
data
```

[16]:
```
         cwc_min   cwc_max   csc_min   csc_max   ctc_min   ctc_max  \
1       0.199996  0.111110  0.799984  0.222221  0.454541  0.151515
2       0.000000  0.000000  0.399992  0.249997  0.249997  0.100000
3       0.999975  0.666656  0.999975  0.444440  0.799992  0.444442
4       0.249994  0.199996  0.666644  0.285710  0.374995  0.249998
5       0.749981  0.599988  0.000000  0.000000  0.599988  0.374995
...          ...       ...       ...       ...       ...       ...
99996   0.333328  0.199998  0.499994  0.285712  0.399997  0.206896
99997   0.599988  0.499992  0.666656  0.666656  0.636358  0.583328
99998   0.714276  0.454541  0.999983  0.599994  0.785709  0.478259
99999   0.749981  0.428565  0.999967  0.428565  0.857131  0.428568
100000  0.999975  0.999975  0.999975  0.999975  0.999988  0.999988

        last_word_eq  first_word_eq  abs_len_diff  mean_len  ...      290_y  \
1                0.0            0.0          22.0      22.0  ... -40.797933
2                0.0            0.0          12.0      14.0  ...  -5.108408
3                0.0            1.0           8.0      14.0  ...  -8.168331
4                0.0            1.0           4.0      10.0  ...  -3.511843
5                0.0            0.0           3.0       6.5  ...  -3.978953
...              ...            ...           ...       ...  ...        ...
99996            0.0            0.0          14.0      22.0  ...   3.245802
99997            1.0            1.0           1.0      11.5  ... -29.309599
99998            0.0            1.0           9.0      18.5  ... -22.722244
99999            0.0            0.0           7.0      10.5  ...   0.176690
100000           1.0            1.0           0.0       8.0  ... -11.794756
```

```
           291_y      292_y     293_y      294_y      295_y      296_y  \
1       8.978392  -8.080880 -5.950699  21.628861   3.837614 -20.311383
2     -12.703356   3.017678 -5.512167  -1.619420   3.469527 -16.574997
3      -7.989178  -6.467180 -1.749593   0.744231   4.275971   5.141163
4       9.312023  11.290786 -4.915463  -9.532688   5.918402  18.655945
5       9.722986   6.704826  2.726543   8.794980  -9.009522 -16.963371
...          ...        ...       ...        ...        ...        ...
99996   0.754974  13.394572 -4.647679  29.584796  -6.857585 -10.416787
99997   3.609023 -10.805955 -3.668922   9.851900  12.539252   0.470887
99998 -10.913383 -17.940394  6.191954  11.269378   1.845742 -13.367261
99999  12.176318  -7.185788 -3.287796   0.360768  11.124272  -0.759304
100000 -2.635185  -2.825474 -1.105005   3.888935  -5.459418   0.219502

          297_y      298_y      299_y
1     -3.942378  32.975520   6.655842
2      3.015558  -2.970531   9.471128
3     -6.298306   0.734777 -10.255797
4     -0.233358  -2.372642  -0.541557
5     -2.120137  -6.946633   5.149253
...         ...        ...        ...
99996  9.078985  20.266087  20.122613
99997  2.304998   2.362773  13.452500
99998 -5.086198   5.820824  16.569165
99999 -5.766187   1.475622  -8.526922
100000 -7.180730  7.596928  14.160029

[100000 rows x 626 columns]
```

[17]:
```
y_true
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4.2.1 Save (serialize) the python object to save second time running

[ ]:
```
# from sklearn.externals import joblib
# joblib.dump(classifier, 'lr_with_more_title_weight_bow_simple_lr_1MM.pkl')
```

```
# classifier = joblib.load('lr_with_more_title_weight_bow_simple_lr_1MM.pkl')
```

[46]:
```
from sklearn.externals import joblib
```

```
/Users/mayankgupta/anaconda3/lib/python3.7/site-
packages/sklearn/externals/joblib/__init__.py:15: DeprecationWarning:
sklearn.externals.joblib is deprecated in 0.21 and will be removed in 0.23.
Please import this functionality directly from joblib, which can be installed
with: pip install joblib. If this warning is raised when loading pickled models,
you may need to re-serialize those models with scikit-learn 0.21+.
  warnings.warn(msg, category=DeprecationWarning)
```

[4]:
```
joblib.dump(data, 'processed_data_with_300_d.pkl')
```

[20]:
```
joblib.dump(y_true, 'class_label_300_d.pkl')
```

[20]:
```
['class_label_300_d.pkl']
```

[47]:
```
data_from_disk = joblib.load('processed_data_with_300_d.pkl')
```

[48]:
```
y_true_from_disk = joblib.load('class_label_300_d.pkl')
```

[49]:
```
data_from_disk
```

[49]:
```
     cwc_min   cwc_max   csc_min   csc_max   ctc_min   ctc_max  \
1   0.199996  0.111110  0.799984  0.222221  0.454541  0.151515
2   0.000000  0.000000  0.399992  0.249997  0.249997  0.100000
3   0.999975  0.666656  0.999975  0.444440  0.799992  0.444442
4   0.249994  0.199996  0.666644  0.285710  0.374995  0.249998
5   0.749981  0.599988  0.000000  0.000000  0.599988  0.374995
6   0.749981  0.749981  0.999980  0.999980  0.888879  0.888879
7   0.333322  0.199996  0.333328  0.249997  0.272725  0.199999
8   0.999967  0.749981  0.749981  0.749981  0.857131  0.749991
9   0.166664  0.083333  0.166664  0.111110  0.142856  0.090909
10  0.749981  0.749981  0.499975  0.333322  0.666656  0.571420
11  0.999980  0.714276  0.833319  0.624992  0.909083  0.666662
12  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
13  0.666644  0.499988  0.666644  0.499988  0.571420  0.571420
14  0.000000  0.000000  0.999950  0.999950  0.499988  0.499988
15  0.999967  0.749981  0.999980  0.999980  0.999988  0.799992
16  0.499975  0.249994  0.000000  0.000000  0.333322  0.249994
17  0.666644  0.399992  0.499988  0.499988  0.571420  0.444440
18  0.999967  0.999967  0.999967  0.599988  0.999983  0.666659
19  0.249994  0.199996  0.749981  0.333330  0.444440  0.285712
20  0.799984  0.799984  0.666644  0.333328  0.666659  0.545450
21  0.333322  0.249994  0.999967  0.749981  0.571420  0.571420
22  0.499988  0.333328  0.199996  0.199996  0.333330  0.272725
23  0.999950  0.999950  0.999967  0.749981  0.999980  0.833319
24  0.000000  0.000000  0.249994  0.249994  0.142855  0.058823
```

25	0.874989	0.874989	0.999986	0.999986	0.933327	0.933327
26	0.666644	0.399992	0.666644	0.333328	0.666656	0.307690
27	0.399992	0.285710	0.333322	0.199996	0.374995	0.249998
28	0.599988	0.272725	0.666656	0.444440	0.499996	0.349998
29	0.749981	0.499992	0.428565	0.299997	0.545450	0.333331
30	0.428565	0.374995	0.599988	0.499992	0.499996	0.399997
...	...	...	...	...	...	...
99971	0.714276	0.624992	0.999983	0.999983	0.785709	0.733328
99972	0.799984	0.799984	0.499988	0.399992	0.666659	0.599994
99973	0.666644	0.666644	0.999975	0.999975	0.857131	0.857131
99974	0.199996	0.199996	0.399992	0.285710	0.299997	0.230767
99975	0.999980	0.555549	0.666656	0.499994	0.818174	0.499997
99976	0.428565	0.374995	0.799984	0.666656	0.538457	0.437497
99977	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
99978	0.857131	0.749991	0.999983	0.999983	0.857137	0.799995
99979	0.666644	0.666644	0.666644	0.399992	0.666656	0.499994
99980	0.499992	0.374995	0.399992	0.249997	0.454541	0.294116
99981	0.999950	0.999950	0.999900	0.499975	0.999967	0.749981
99982	0.666644	0.666644	0.799984	0.799984	0.749991	0.666659
99983	0.749981	0.599988	0.999975	0.999975	0.874989	0.699993
99984	0.888879	0.888879	0.999990	0.999990	0.899996	0.899996
99985	0.749981	0.599988	0.666644	0.499988	0.714276	0.555549
99986	0.999950	0.666644	0.499975	0.249994	0.749981	0.428565
99987	0.166664	0.124998	0.000000	0.000000	0.099999	0.058823
99988	0.499994	0.499994	0.249994	0.199996	0.416663	0.357140
99989	0.399992	0.399992	0.000000	0.000000	0.222220	0.181817
99990	0.499992	0.272725	0.499992	0.199999	0.499996	0.214285
99991	0.749981	0.749981	0.749981	0.749981	0.749991	0.749991
99992	0.999950	0.666644	0.749981	0.599988	0.714276	0.624992
99993	0.000000	0.000000	0.166664	0.166664	0.099999	0.066666
99994	0.000000	0.000000	0.249994	0.199996	0.083333	0.076922
99995	0.399992	0.399992	0.199996	0.166664	0.299997	0.272725
99996	0.333328	0.199998	0.499994	0.285712	0.399997	0.206896
99997	0.599988	0.499992	0.666656	0.666656	0.636358	0.583328
99998	0.714276	0.454541	0.999983	0.599994	0.785709	0.478259
99999	0.749981	0.428565	0.999967	0.428565	0.857131	0.428568
100000	0.999975	0.999975	0.999975	0.999975	0.999988	0.999988

	last_word_eq	first_word_eq	abs_len_diff	mean_len	...	290_y	\
1	0.0	0.0	22.0	22.0	...	-40.797933	
2	0.0	0.0	12.0	14.0	...	-5.108408	
3	0.0	1.0	8.0	14.0	...	-8.168331	
4	0.0	1.0	4.0	10.0	...	-3.511843	
5	0.0	0.0	3.0	6.5	...	-3.978953	
6	1.0	1.0	0.0	9.0	...	-1.338060	
7	0.0	0.0	4.0	13.0	...	-6.030159	
8	1.0	1.0	1.0	7.5	...	-7.301916	

9	0.0	0.0	8.0	18.0	...	-8.063692
10	0.0	1.0	1.0	6.5	...	5.330708
11	1.0	0.0	4.0	13.0	...	-13.392167
12	0.0	0.0	21.0	17.5	...	-9.997019
13	1.0	1.0	0.0	7.0	...	-15.134821
14	0.0	1.0	0.0	4.0	...	2.901961
15	1.0	1.0	2.0	9.0	...	8.528523
16	0.0	0.0	1.0	3.5	...	3.384561
17	1.0	1.0	2.0	8.0	...	-7.667511
18	0.0	1.0	3.0	7.5	...	-13.152355
19	0.0	1.0	5.0	11.5	...	-3.844284
20	1.0	0.0	2.0	10.0	...	8.863629
21	0.0	1.0	0.0	7.0	...	2.537473
22	0.0	1.0	2.0	10.0	...	-9.803080
23	1.0	1.0	1.0	5.5	...	-3.643097
24	0.0	0.0	10.0	12.0	...	-15.271290
25	0.0	1.0	0.0	15.0	...	1.306528
26	0.0	0.0	7.0	9.5	...	-3.854654
27	0.0	0.0	4.0	10.0	...	-4.118912
28	0.0	0.0	6.0	17.0	...	-6.200628
29	0.0	0.0	7.0	14.5	...	-8.448265
30	0.0	0.0	3.0	13.5	...	-21.526779
...	...	...	...	...	...	...
99971	1.0	1.0	1.0	14.5	...	-1.109346
99972	0.0	1.0	1.0	9.5	...	-7.005068
99973	1.0	1.0	0.0	7.0	...	-3.239349
99974	0.0	1.0	3.0	11.5	...	-7.694058
99975	0.0	0.0	7.0	14.5	...	-1.676436
99976	0.0	1.0	3.0	14.5	...	4.847804
99977	0.0	0.0	2.0	6.0	...	-3.092498
99978	0.0	1.0	1.0	14.5	...	-9.642987
99979	1.0	1.0	2.0	7.0	...	-3.094555
99980	0.0	0.0	6.0	14.0	...	-34.678211
99981	1.0	0.0	1.0	3.5	...	-6.026102
99982	1.0	1.0	1.0	8.5	...	-9.770888
99983	0.0	1.0	2.0	9.0	...	3.859976
99984	0.0	1.0	0.0	20.0	...	-7.587582
99985	1.0	0.0	2.0	8.0	...	-4.054505
99986	1.0	1.0	3.0	5.5	...	-29.770070
99987	0.0	0.0	7.0	13.5	...	1.816878
99988	0.0	1.0	2.0	13.0	...	-23.477808
99989	1.0	0.0	2.0	10.0	...	19.992479
99990	0.0	0.0	16.0	20.0	...	-31.095683
99991	0.0	1.0	0.0	8.0	...	-4.012943
99992	1.0	0.0	1.0	7.5	...	-2.561741
99993	0.0	0.0	5.0	12.5	...	-1.011837
99994	0.0	0.0	1.0	12.5	...	-4.584122

99995	0.0	0.0	1.0	10.5	...	-1.979724
99996	0.0	0.0	14.0	22.0	...	3.245802
99997	1.0	1.0	1.0	11.5	...	-29.309599
99998	0.0	1.0	9.0	18.5	...	-22.722244
99999	0.0	0.0	7.0	10.5	...	0.176690
100000	1.0	1.0	0.0	8.0	...	-11.794756

	291_y	292_y	293_y	294_y	295_y	296_y \
1	8.978392	-8.080880	-5.950699	21.628861	3.837614	-20.311383
2	-12.703356	3.017678	-5.512167	-1.619420	3.469527	-16.574997
3	-7.989178	-6.467180	-1.749593	0.744231	4.275971	5.141163
4	9.312023	11.290786	-4.915463	-9.532688	5.918402	18.655945
5	9.722986	6.704826	2.726543	8.794980	-9.009522	-16.963371
6	-2.847187	3.591076	2.681107	-1.502780	8.135663	-6.245612
7	0.442590	9.012010	-5.150438	-8.492141	2.556222	-3.526519
8	6.071443	2.322339	-5.996986	-2.572389	2.892691	-7.748424
9	3.856235	-0.445077	-3.855534	0.291414	1.276975	-5.668518
10	-1.176866	-4.973069	-15.590182	-2.342324	5.010971	-14.394878
11	10.290797	2.474590	3.741205	6.824369	9.697411	4.609283
12	6.162037	0.429386	4.145748	-3.129390	-3.373795	-1.328999
13	9.288846	-3.124745	-0.979933	2.559292	-12.344372	-0.680858
14	0.051307	-1.327939	0.439503	1.035125	6.172948	-0.856086
15	-1.789429	-3.661613	2.848219	6.925925	-2.540502	-2.712150
16	-1.944733	-2.046885	10.050879	8.219749	-2.323018	-1.828770
17	4.700181	-6.699899	-0.283859	2.856647	1.153833	-0.409437
18	-1.252878	-3.562230	-5.232966	-4.569258	5.098299	-6.180748
19	-9.622576	-1.163764	-6.678519	4.847170	11.256170	-13.831446
20	6.349486	-3.015467	-8.659005	-9.718475	3.955955	-0.826360
21	-2.371000	-6.413624	-0.321854	0.076716	6.329403	-2.417905
22	-4.989100	3.551733	-4.187442	-9.000243	0.570971	-6.008328
23	2.971763	-3.521338	-3.156078	3.636689	-1.839536	-0.237346
24	-14.639240	4.390267	-35.626108	-2.840115	-0.109183	20.197851
25	-1.984461	-3.986665	2.163000	1.672606	-2.883575	-20.462159
26	-1.719057	0.035982	-4.267324	-6.375755	1.537614	-6.879949
27	11.426763	8.173534	-8.410315	13.350192	0.442050	3.555014
28	-2.907248	-13.097898	3.286459	15.316685	30.233097	9.858233
29	2.249638	5.682299	0.103268	19.533324	-0.477940	-4.985020
30	-2.667890	0.154728	-15.339074	-4.590981	25.891446	-11.441289
...	...	...	...	...	...	...
99971	1.899697	1.788559	12.521784	17.121484	-6.543861	-5.392328
99972	-0.813220	-0.299529	2.435843	4.648860	-2.050572	-6.245761
99973	1.671365	-3.844518	-0.945203	3.915918	0.362138	-6.221982
99974	9.868406	11.076913	-4.558292	-5.110034	7.964354	-0.887783
99975	-0.352912	-4.557141	1.363794	-10.048533	-0.014637	-6.210315
99976	3.578397	-9.942549	-3.644479	-12.520845	-5.309959	4.513854
99977	-11.952529	-1.958051	6.768930	10.893866	-16.778309	3.888398
99978	-7.191664	-2.733143	5.692765	20.842203	-1.762962	-3.933575

99979	0.445148	-3.663525	-4.165020	0.521401	1.169381	-1.954160
99980	8.015239	4.266977	-2.942691	7.536032	13.628954	-14.941270
99981	2.859484	-17.317383	-2.885169	-4.530976	-2.307037	-5.741133
99982	-9.458455	-0.342100	-3.170780	6.448980	3.408721	-4.062496
99983	-5.385239	-7.831124	3.195311	9.257507	4.083518	3.709167
99984	16.736711	3.758538	8.303743	16.023457	-3.029131	-4.461002
99985	3.011667	-3.237565	-4.793032	6.936227	3.985816	3.695235
99986	-5.922200	6.758135	3.488054	-11.406006	0.540253	13.845514
99987	0.831103	-0.171582	-1.921083	-5.081946	-3.667437	-10.234903
99988	1.688032	-3.438001	-9.625710	1.774994	-14.946189	-8.702157
99989	-1.372286	-4.581258	-20.772952	-12.682971	13.347009	14.797641
99990	-4.929975	-9.584140	-16.577436	0.971738	-14.226957	-17.343335
99991	2.930883	-5.783331	-4.215518	10.654501	-8.094253	0.685942
99992	2.082029	-6.961860	-0.945801	-0.409064	0.159778	-10.960458
99993	-0.112020	-7.876893	-1.486276	-6.287929	7.313586	-5.491764
99994	-8.467183	-1.634740	-6.641861	7.653582	-0.987677	-8.216270
99995	-1.927612	-7.765022	-10.304489	-6.876469	-6.360809	3.879852
99996	0.754974	13.394572	-4.647679	29.584796	-6.857585	-10.416787
99997	3.609023	-10.805955	-3.668922	9.851900	12.539252	0.470887
99998	-10.913383	-17.940394	6.191954	11.269378	1.845742	-13.367261
99999	12.176318	-7.185788	-3.287796	0.360768	11.124272	-0.759304
100000	-2.635185	-2.825474	-1.105005	3.888935	-5.459418	0.219502

	297_y	298_y	299_y
1	-3.942378	32.975520	6.655842
2	3.015558	-2.970531	9.471128
3	-6.298306	0.734777	-10.255797
4	-0.233358	-2.372642	-0.541557
5	-2.120137	-6.946633	5.149253
6	7.110384	-9.560786	-0.008232
7	9.001639	-4.847330	4.309788
8	-1.177841	-4.149691	-8.250180
9	-6.244662	8.020668	10.943929
10	-5.150761	-0.733505	-4.396690
11	0.634063	-10.236621	4.588567
12	2.780580	2.607424	0.716233
13	-0.747220	1.721723	-1.543272
14	0.319795	1.585563	7.493772
15	-2.016891	-0.122290	16.067184
16	-8.561517	1.242106	1.190385
17	0.393342	1.529846	1.973178
18	-5.653592	3.626891	6.377751
19	0.424530	0.440655	0.121351
20	-3.185053	5.068665	7.845967
21	-8.436717	7.809141	7.074978
22	-3.208273	-1.360039	0.590830
23	0.420066	-1.510369	4.100976

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24        7.903590   7.993767 -12.496622
25        1.382380  -2.172366   5.826740
26        0.569165   1.141381   6.988508
27       -2.369264  -9.543604  14.371956
28        3.363049  -0.147895   7.143345
29       -4.194356  -4.533633   8.543751
30      -11.720306  -2.166472  -4.215963
...            ...        ...        ...
99971    -1.570295  -3.005336  -2.555033
99972    -7.955970  -4.115861   8.152022
99973    -0.629472   5.967974   3.852626
99974     3.868106   4.934638  13.009006
99975     2.440044  -7.659449   0.917944
99976   -21.040953  10.786055  19.606563
99977    -7.947600  -1.422062   1.173117
99978    -4.173814 -12.239999  10.293721
99979     0.915726   4.369510   3.396921
99980   -11.611394   0.133652  -6.719521
99981     5.207395  -5.498207  -6.418999
99982     4.166325   1.512058  -4.918114
99983    -7.189160  -4.965273   6.210760
99984    21.124996   8.343070  10.188382
99985     0.923180   3.030959   2.870284
99986     0.864665  20.155358  24.729774
99987     0.626981  11.975883   5.783221
99988   -17.430611  -9.927815   9.510970
99989    -3.958943  13.093280  -9.624306
99990     0.129029   5.133360  20.662685
99991    -2.435648   7.676443   6.067093
99992    -4.940494   0.009893  -0.598740
99993   -13.710724   3.378671   4.360688
99994    14.953423   2.496999   6.259324
99995     0.734775  -2.015996   5.778946
99996     9.078985  20.266087  20.122613
99997     2.304998   2.362773  13.452500
99998    -5.086198   5.820824  16.569165
99999    -5.766187   1.475622  -8.526922
100000   -7.180730   7.596928  14.160029

[100000 rows x 626 columns]
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y_true_from_disk
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[51]:
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data = data_from_disk
y_true = y_true_from_disk
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4.3 Random train test split(70:30)

[52]:
```
X_train,X_test, y_train, y_test = train_test_split(data, y_true,␣
↪stratify=y_true, test_size=0.3)
```

[53]:
```
print("Number of data points in train data :",X_train.shape)
print("Number of data points in test data :",X_test.shape)
```

```
Number of data points in train data : (70000, 626)
Number of data points in test data : (30000, 626)
```

[54]:
```
print("-"*10, "Distribution of output variable in train data", "-"*10)
train_distr = Counter(y_train)
train_len = len(y_train)
print("Class 0: ",int(train_distr[0])/train_len,"Class 1: ",␣
↪int(train_distr[1])/train_len)
print("-"*10, "Distribution of output variable in train data", "-"*10)
test_distr = Counter(y_test)
test_len = len(y_test)
print("Class 0: ",int(test_distr[1])/test_len, "Class 1: ",int(test_distr[1])/
↪test_len)
```

```
---------- Distribution of output variable in train data ----------
Class 0:  0.6311857142857142 Class 1:  0.3688142857142857
---------- Distribution of output variable in train data ----------
Class 0:  0.3688 Class 1:  0.3688
```

[3]:
```
# This function plots the confusion matrices given y_i, y_i_hat.
def plot_confusion_matrix(test_y, predict_y):
    C = confusion_matrix(test_y, predict_y)
    # C = 9,9 matrix, each cell (i,j) represents number of points of class i␣
↪are predicted class j

    A =(((C.T)/(C.sum(axis=1))).T)
    #divid each element of the confusion matrix with the sum of elements in␣
↪that column
```

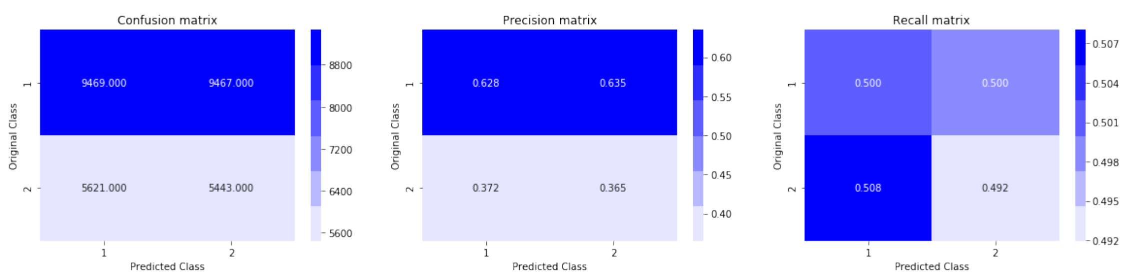
```
    # C = [[1, 2],
    #      [3, 4]]
    # C.T = [[1, 3],
    #        [2, 4]]
    # C.sum(axis = 1)  axis=0 corresonds to columns and axis=1 corresponds to␣
↪rows in two diamensional array
    # C.sum(axix =1) = [[3, 7]]
    # ((C.T)/(C.sum(axis=1))) = [[1/3, 3/7]
    #                            [2/3, 4/7]]

    # ((C.T)/(C.sum(axis=1))).T = [[1/3, 2/3]
    #                            [3/7, 4/7]]
    # sum of row elements = 1

    B =(C/C.sum(axis=0))
    #divid each element of the confusion matrix with the sum of elements in␣
↪that row
    # C = [[1, 2],
    #      [3, 4]]
    # C.sum(axis = 0)  axis=0 corresonds to columns and axis=1 corresponds to␣
↪rows in two diamensional array
    # C.sum(axix =0) = [[4, 6]]
    # (C/C.sum(axis=0)) = [[1/4, 2/6],
    #                       [3/4, 4/6]]
    plt.figure(figsize=(20,4))

    labels = [1,2]
    # representing A in heatmap format
    cmap=sns.light_palette("blue")
    plt.subplot(1, 3, 1)
    sns.heatmap(C, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels,␣
↪yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Confusion matrix")

    plt.subplot(1, 3, 2)
    sns.heatmap(B, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels,␣
↪yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Precision matrix")

    plt.subplot(1, 3, 3)
    # representing B in heatmap format
```

```
    sns.heatmap(A, annot=True, cmap=cmap, fmt=".3f", xticklabels=labels,␣
↪yticklabels=labels)
    plt.xlabel('Predicted Class')
    plt.ylabel('Original Class')
    plt.title("Recall matrix")

    plt.show()
```

4.4 Building a random model (Finding worst-case log-loss)

[30]:
```
start = dt.datetime.now()
# we need to generate 9 numbers and the sum of numbers should be 1
# one solution is to genarate 9 numbers and divide each of the numbers by their␣
↪sum
# ref: https://stackoverflow.com/a/18662466/4084039
# we create a output array that has exactly same size as the CV data
predicted_y = np.zeros((test_len,2))
for i in range(test_len):
    rand_probs = np.random.rand(1,2)
    predicted_y[i] = ((rand_probs/sum(sum(rand_probs)))[0])
print("Log loss on Test Data using Random Model",log_loss(y_test, predicted_y,␣
↪eps=1e-15))

predicted_y =np.argmax(predicted_y, axis=1)
plot_confusion_matrix(y_test, predicted_y)
print('Total time taken to run this cell: ', dt.datetime.now()-start)
```

```
Log loss on Test Data using Random Model 0.8905921124455075
```




```
Total time taken to run this cell:  0:00:00.841952
```

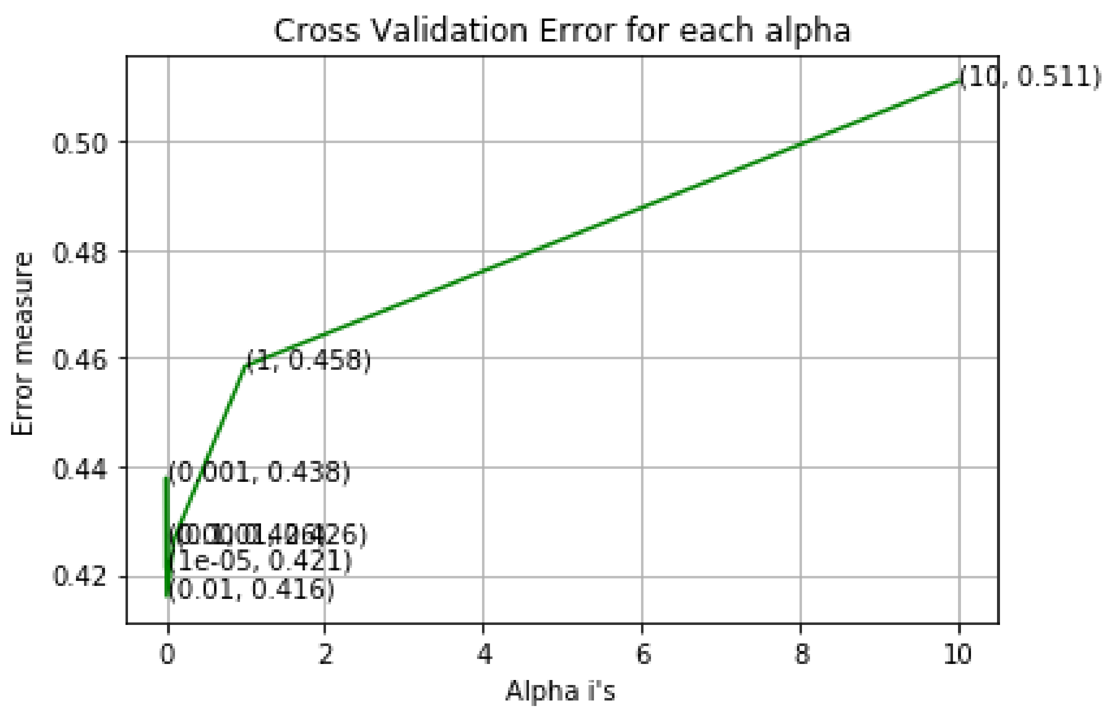
4.4 Logistic Regression with hyperparameter tuning

[31]:
```
start = dt.datetime.now()
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/
↪generated/sklearn.linear_model.SGDClassifier.html
```

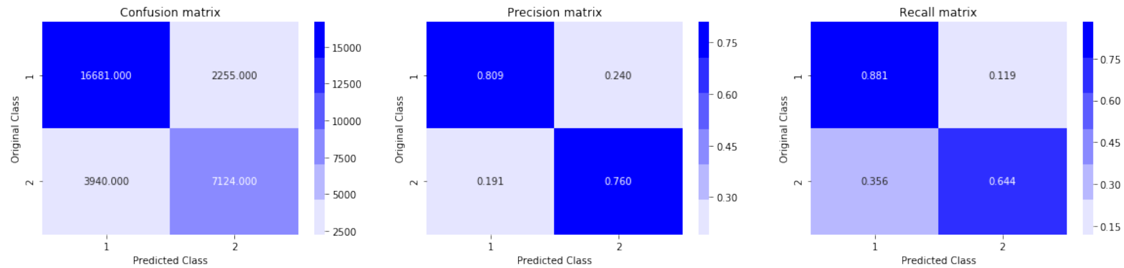
```
# -------------------------------
# default parameters
# SGDClassifier(loss=hinge, penalty=l2, alpha=0.0001, l1_ratio=0.15,␣
↪fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None,␣
↪learning_rate=optimal, eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, ])        Fit linear model with␣
↪Stochastic Gradient Descent.
# predict(X)        Predict class labels for samples in X.

#-------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42)
    clf.fit(X_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    predict_y = sig_clf.predict_proba(X_test)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_,␣
↪eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test,␣
↪predict_y, labels=clf.classes_, eps=1e-15))

fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='log',␣
↪random_state=42)
clf.fit(X_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
```

```
sig_clf.fit(X_train, y_train)

predict_y = sig_clf.predict_proba(X_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:
 ↪",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:
 ↪",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
print('Total time taken to run this cell: ', dt.datetime.now()-start)
```

```
For values of alpha =  1e-05 The log loss is: 0.42132882548668504
For values of alpha =  0.0001 The log loss is: 0.42604496228022365
For values of alpha =  0.001 The log loss is: 0.4378636962419774
For values of alpha =  0.01 The log loss is: 0.41597950083313784
For values of alpha =  0.1 The log loss is: 0.4263936710243334
For values of alpha =  1 The log loss is: 0.45844682837382617
For values of alpha =  10 The log loss is: 0.5109492989543734
```




```
For values of best alpha =  0.01 The train log loss is: 0.40789399542051274
For values of best alpha =  0.01 The test log loss is: 0.41597950083313784
Total number of data points : 30000
```



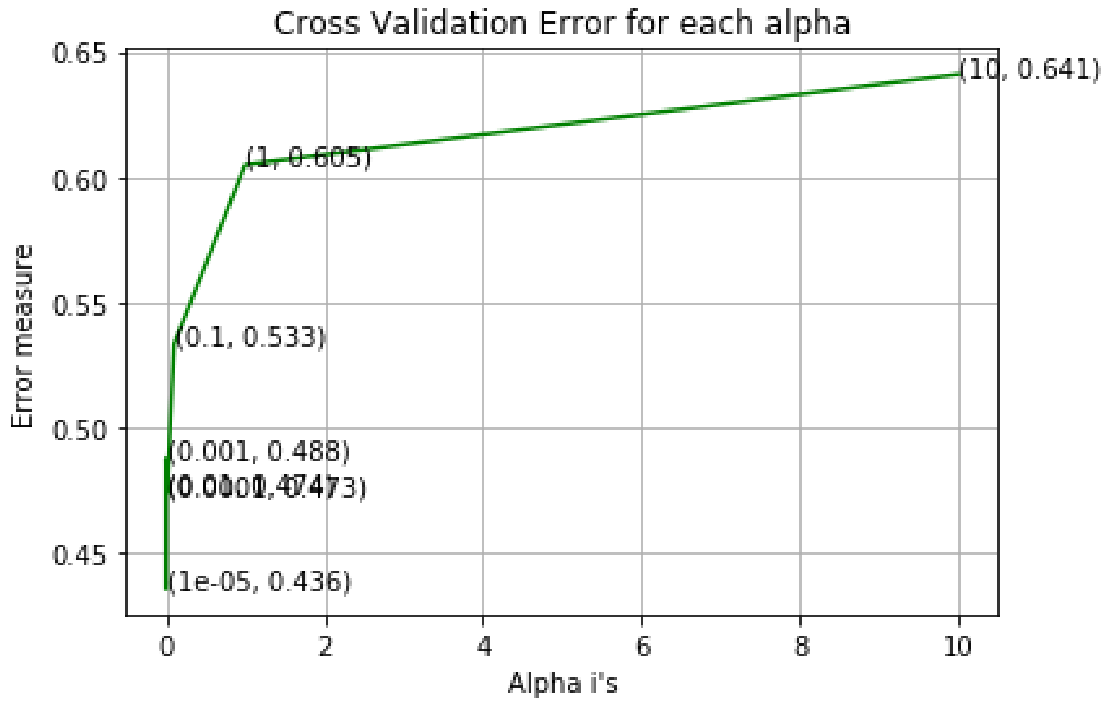

```
Total time taken to run this cell:  0:16:27.569972
```

4.5 Linear SVM with hyperparameter tuning

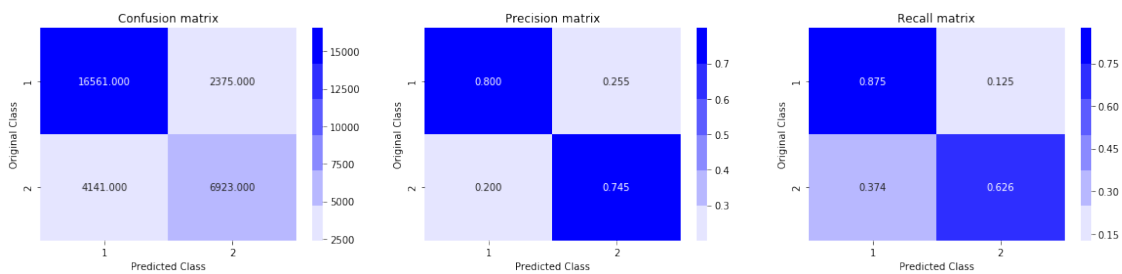
[15]:
```
start = dt.datetime.now()
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/
↪generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss=hinge, penalty=l2, alpha=0.0001, l1_ratio=0.15,␣
↪fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None,␣
↪learning_rate=optimal, eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, ])        Fit linear model with␣
↪Stochastic Gradient Descent.
# predict(X)        Predict class labels for samples in X.

#-------------------------------
# video link:
#------------------------------



log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l1', loss='hinge', random_state=42)
    clf.fit(X_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(X_train, y_train)
    predict_y = sig_clf.predict_proba(X_test)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_,␣
↪eps=1e-15))
```

```
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test,␣
 ↪predict_y, labels=clf.classes_, eps=1e-15))

fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l1', loss='hinge',␣
 ↪random_state=42)
clf.fit(X_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(X_train, y_train)

predict_y = sig_clf.predict_proba(X_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:
 ↪",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(X_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:
 ↪",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
print('Total time taken to run this cell: ', dt.datetime.now()-start)
```

```
For values of alpha =  1e-05 The log loss is: 0.4358909709856658
For values of alpha =  0.0001 The log loss is: 0.47325600678254653
For values of alpha =  0.001 The log loss is: 0.487724484742427
For values of alpha =  0.01 The log loss is: 0.4743403564077363
For values of alpha =  0.1 The log loss is: 0.5334469886637074
For values of alpha =  1 The log loss is: 0.604869393207471
For values of alpha =  10 The log loss is: 0.6409528719264598
```




```
For values of best alpha =  1e-05 The train log loss is: 0.4346314662369074
For values of best alpha =  1e-05 The test log loss is: 0.4358909709856658
Total number of data points : 30000
```




```
Total time taken to run this cell:  2:07:21.787953
```

4.6 XGBoost

[16]:
```
start = dt.datetime.now()
import xgboost as xgb
params = {}
params['objective'] = 'binary:logistic'
params['eval_metric'] = 'logloss'
params['eta'] = 0.02
```

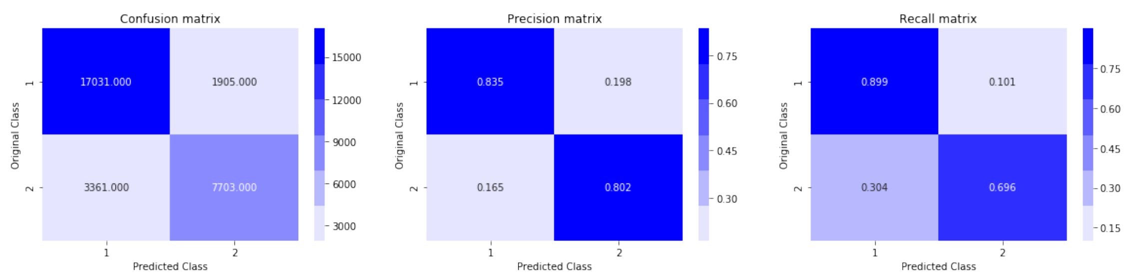
```
params['max_depth'] = 4

d_train = xgb.DMatrix(X_train, label=y_train)
d_test = xgb.DMatrix(X_test, label=y_test)

watchlist = [(d_train, 'train'), (d_test, 'valid')]

bst = xgb.train(params, d_train, 400, watchlist, early_stopping_rounds=20,␣
 ↪verbose_eval=10)

xgdmat = xgb.DMatrix(X_train,y_train)
predict_y = bst.predict(d_test)
print("The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_,␣
 ↪eps=1e-15))
```

```
[0]     train-logloss:0.684813  valid-logloss:0.684885
Multiple eval metrics have been passed: 'valid-logloss' will be used for early
stopping.

Will train until valid-logloss hasn't improved in 20 rounds.
[10]    train-logloss:0.614904  valid-logloss:0.615185
[20]    train-logloss:0.563579  valid-logloss:0.564123
[30]    train-logloss:0.525489  valid-logloss:0.526226
[40]    train-logloss:0.495926  valid-logloss:0.496874
[50]    train-logloss:0.473081  valid-logloss:0.474175
[60]    train-logloss:0.454754  valid-logloss:0.455969
[70]    train-logloss:0.440157  valid-logloss:0.441437
[80]    train-logloss:0.428395  valid-logloss:0.429883
[90]    train-logloss:0.418717  valid-logloss:0.420335
[100]   train-logloss:0.410756  valid-logloss:0.412517
[110]   train-logloss:0.404025  valid-logloss:0.405925
[120]   train-logloss:0.398363  valid-logloss:0.400391
[130]   train-logloss:0.393669  valid-logloss:0.395812
[140]   train-logloss:0.389762  valid-logloss:0.392067
[150]   train-logloss:0.386098  valid-logloss:0.388622
[160]   train-logloss:0.382895  valid-logloss:0.385655
[170]   train-logloss:0.380258  valid-logloss:0.383215
[180]   train-logloss:0.377816  valid-logloss:0.381036
[190]   train-logloss:0.375544  valid-logloss:0.378998
[200]   train-logloss:0.373367  valid-logloss:0.377096
[210]   train-logloss:0.371304  valid-logloss:0.375283
[220]   train-logloss:0.369262  valid-logloss:0.373548
[230]   train-logloss:0.367263  valid-logloss:0.371818
[240]   train-logloss:0.365543  valid-logloss:0.37044
[250]   train-logloss:0.363863  valid-logloss:0.369073
[260]   train-logloss:0.362203  valid-logloss:0.367772
[270]   train-logloss:0.360698  valid-logloss:0.366575
```

```
[280]   train-logloss:0.359275  valid-logloss:0.365413
[290]   train-logloss:0.357806  valid-logloss:0.364322
[300]   train-logloss:0.35648   valid-logloss:0.363363
[310]   train-logloss:0.355206  valid-logloss:0.362425
[320]   train-logloss:0.353887  valid-logloss:0.361486
[330]   train-logloss:0.352583  valid-logloss:0.360547
[340]   train-logloss:0.351331  valid-logloss:0.359649
[350]   train-logloss:0.350246  valid-logloss:0.358922
[360]   train-logloss:0.349085  valid-logloss:0.358083
[370]   train-logloss:0.347877  valid-logloss:0.357233
[380]   train-logloss:0.34682   valid-logloss:0.356554
[390]   train-logloss:0.345695  valid-logloss:0.355809
[399]   train-logloss:0.344806  valid-logloss:0.35524
The test log loss is: 0.3552402963906119
```

[17]:
```
predicted_y =np.array(predict_y>0.5,dtype=int)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
print('Total time taken to run this cell: ', dt.datetime.now()-start)
```

```
Total number of data points : 30000
```




```
Total time taken to run this cell:  0:10:40.845603
```

4.7 Models Output

[19]:
```
from prettytable import PrettyTable

table = PrettyTable()

table.field_names = ['Model', 'Hyperparameter', 'Log-Loss']

table.add_row(['Random Model', None, 0.8905921124455075])
table.add_row(['Logistic Regression', 0.01, 0.415979500833137 84])
table.add_row(['Linear SVM', 1e-05, 0.4358909709856658])
table.add_row(['Xgboost', 'MaxDepth:4,eta:0.02', 0.3552402963906119])
```

```
print(table)
```

```
+----------------------+----------------------+----------------------+
|        Model         |    Hyperparameter    |       Log-Loss       |
+----------------------+----------------------+----------------------+
|     Random Model     |         None         |  0.8905921124455075  |
| Logistic Regression  |         0.01         | 0.41597950083313784  |
|      Linear SVM      |        1e-05         |  0.4358909709856658  |
|       Xgboost        | MaxDepth:4,eta:0.02  |  0.3552402963906119  |
+----------------------+----------------------+----------------------+
```

5. Assignments

1. Try out models (Logistic regression, Linear-SVM) with simple TF-IDF vectors instead of TD_IDF weighted word2Vec.
2. Hyperparameter tune XgBoost using RandomSearch to reduce the log-loss.

5.1 Try out models (Logistic regression, Linear-SVM) with simple TF-IDF vectors instead of TD_IDF weighted word2Vec.

[2]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
```

5.1.1 TFIDF Based Features

[3]:
```
# avoid decoding problems
df = pd.read_csv("train.csv")

# encode questions to unicode
# https://stackoverflow.com/a/6812069
# ----------------- python 2 ---------------------
# df['question1'] = df['question1'].apply(lambda x: unicode(str(x),"utf-8"))
# df['question2'] = df['question2'].apply(lambda x: unicode(str(x),"utf-8"))
# ----------------- python 3 ---------------------
df['question1'] = df['question1'].apply(lambda x: str(x))
df['question2'] = df['question2'].apply(lambda x: str(x))
```

[4]:
```
df.head()
```

[4]:
```
   id  qid1  qid2                                         question1  \
0   0     1     2  What is the step by step guide to invest in sh...
1   1     3     4  What is the story of Kohinoor (Koh-i-Noor) Dia...
2   2     5     6  How can I increase the speed of my internet co...
3   3     7     8  Why am I mentally very lonely? How can I solve...
4   4     9    10  Which one dissolve in water quikly sugar, salt...

                                           question2  is_duplicate
0  What is the step by step guide to invest in sh...             0
1  What would happen if the Indian government sto...             0
2  How can Internet speed be increased by hacking...             0
3  Find the remainder when [math]23^{24}[/math] i...             0
```

```
4            Which fish would survive in salt water?            0
```

[5]:
```python
df.shape
```

[5]:
```
(404290, 6)
```

[6]:
```python
# define train and test length (100000 = 80000+20000)
train_len = 80000
test_len = 20000
```

[7]:
```python
# prepare test and train data
q1_train_data = df['question1'][0:train_len].copy()
q1_test_data = df['question1'][train_len:train_len+test_len].copy()
q2_train_data = df['question2'][0:train_len].copy()
q2_test_data = df['question2'][train_len:train_len+test_len].copy()
```

[8]:
```python
q1_train_data.head()
```

[8]:
```
0    What is the step by step guide to invest in sh...
1    What is the story of Kohinoor (Koh-i-Noor) Dia...
2    How can I increase the speed of my internet co...
3    Why am I mentally very lonely? How can I solve...
4    Which one dissolve in water quikly sugar, salt...
Name: question1, dtype: object
```

[9]:
```python
q1_test_data.head()
```

[9]:
```
80000        How do I recover deleted files in an Android?
80001                    What are some good start up ideas?
80002    What reason does philosophy give for our exist...
80003    What are the differences between a sociopath a...
80004    How do I talk to my parents to give me more fr...
Name: question1, dtype: object
```

[10]:
```python
q2_train_data.head()
```

[10]:
```
0    What is the step by step guide to invest in sh...
1    What would happen if the Indian government sto...
2    How can Internet speed be increased by hacking...
3    Find the remainder when [math]23^{24}[/math] i...
4              Which fish would survive in salt water?
Name: question2, dtype: object
```

[11]:
```python
q2_test_data.head()
```

[11]:
```
80000    How do I recover deleted files on an Android p...
80001                   What is the best start up to start?
80002    How much income can I generate by selling an e...
80003    What are the trait differences of a sociopath ...
80004             How do I start talking more to my parents?
Name: question2, dtype: object
```

[12]:
```
# merge texts
questions = list(q1_train_data) + list(q2_train_data)
```

[13]:
```
# fit TfidfVectorizer on whole train vocabulary
tfidf = TfidfVectorizer(lowercase=False, ngram_range=(1,2))
tfidf.fit(questions)
```

[13]:
```
TfidfVectorizer(analyzer='word', binary=False, decode_error='strict',
                dtype=<class 'numpy.float64'>, encoding='utf-8',
                input='content', lowercase=False, max_df=1.0, max_features=None,
                min_df=1, ngram_range=(1, 2), norm='l2', preprocessor=None,
                smooth_idf=True, stop_words=None, strip_accents=None,
                sublinear_tf=False, token_pattern='(?u)\\b\\w\\w+\\b',
                tokenizer=None, use_idf=True, vocabulary=None)
```

[14]:
```
q1_train_data_vector = tfidf.transform(q1_train_data.values.tolist())
q1_test_data_vector = tfidf.transform(q1_test_data.values.tolist())
q2_train_data_vector = tfidf.transform(q2_train_data.values.tolist())
q2_test_data_vector = tfidf.transform(q2_test_data.values.tolist())
```

[15]:
```
print("Shape of Question1 Data:", q1_train_data_vector.shape,␣
 ↪q1_test_data_vector.shape)
print("Shape of Question2 Data:", q2_train_data_vector.shape,␣
 ↪q2_test_data_vector.shape)
```

```
Shape of Question1 Data: (80000, 475311) (20000, 475311)
Shape of Question2 Data: (80000, 475311) (20000, 475311)
```

[16]:
```
from scipy.sparse import hstack
```

[17]:
```
x_train_ques = hstack([q1_train_data_vector, q2_train_data_vector])
x_test_ques = hstack([q1_test_data_vector, q2_test_data_vector])
```

[18]:
```
x_train_ques.shape, x_test_ques.shape
```

[18]:
```
((80000, 950622), (20000, 950622))
```

[19]:
```
df = df.head(100000)
```

[20]:
```
df.columns
```

[20]:
```
Index(['id', 'qid1', 'qid2', 'question1', 'question2', 'is_duplicate'],
dtype='object')
```

[21]:
```
y_train = df['is_duplicate'][0:train_len].values.tolist()
y_test = df['is_duplicate'][train_len:train_len+test_len].values.tolist()
```

[22]:
```
len(y_train), len(y_test)
```

[22]:
```
(80000, 20000)
```

[23]:
```
y_train[0:10]
```

[23]:
```
[0, 0, 0, 0, 0, 1, 0, 1, 0, 0]
```

[24]:
```
y_test[0:10]
```

[24]:
```
[1, 1, 0, 1, 0, 0, 1, 0, 0, 1]
```

[25]:
```
a = df['is_duplicate'][80000:5+80000].values.tolist()
a
```

[25]:
```
[1, 1, 0, 1, 0]
```

[26]:
```
#prepro_features_train.csv (Simple Preprocessing Feartures)
#nlp_features_train.csv (NLP Features)
if os.path.isfile('nlp_features_train.csv'):
    dfnlp = pd.read_csv("nlp_features_train.csv",encoding='latin-1')
else:
    print("download nlp_features_train.csv from drive or run previous notebook")

if os.path.isfile('df_fe_without_preprocessing_train.csv'):
    dfppro = pd.read_csv("df_fe_without_preprocessing_train.
 ↪csv",encoding='latin-1')
else:
    print("download df_fe_without_preprocessing_train.csv from drive or run␣
 ↪previous notebook")
```

[27]:
```
df1 = dfnlp.drop(['qid1','qid2','question1','question2'],axis=1)
df2 = dfppro.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
df3 = df.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
# df3_q1 = pd.DataFrame(df3.q1_feats_m.values.tolist(), index= df3.index)
# df3_q2 = pd.DataFrame(df3.q2_feats_m.values.tolist(), index= df3.index)

df1.columns, df2.columns, df3.columns
```

[27]:
```
(Index(['id', 'is_duplicate', 'cwc_min', 'cwc_max', 'csc_min', 'csc_max',
        'ctc_min', 'ctc_max', 'last_word_eq', 'first_word_eq', 'abs_len_diff',
        'mean_len', 'token_set_ratio', 'token_sort_ratio', 'fuzz_ratio',
        'fuzz_partial_ratio', 'longest_substr_ratio'],
       dtype='object'),
 Index(['id', 'freq_qid1', 'freq_qid2', 'q1len', 'q2len', 'q1_n_words',
        'q2_n_words', 'word_Common', 'word_Total', 'word_share', 'freq_q1+q2',
        'freq_q1-q2'],
       dtype='object'),
 Index(['id'], dtype='object'))
```

[28]:
```
df1 = df1.drop(['id', 'is_duplicate'], axis=1)
df2 = df2.drop(['id'], axis=1)

df1.columns, df2.columns
```

[28]:
```
(Index(['cwc_min', 'cwc_max', 'csc_min', 'csc_max', 'ctc_min', 'ctc_max',
        'last_word_eq', 'first_word_eq', 'abs_len_diff', 'mean_len',
        'token_set_ratio', 'token_sort_ratio', 'fuzz_ratio',
        'fuzz_partial_ratio', 'longest_substr_ratio'],
```

```
       dtype='object'),
 Index(['freq_qid1', 'freq_qid2', 'q1len', 'q2len', 'q1_n_words', 'q2_n_words',
        'word_Common', 'word_Total', 'word_share', 'freq_q1+q2', 'freq_q1-q2'],
       dtype='object'))
```

[29]:
```
df1.head()
```

[29]:
```
    cwc_min   cwc_max   csc_min   csc_max   ctc_min   ctc_max  last_word_eq  \
0  0.999980  0.833319  0.999983  0.999983  0.916659  0.785709           0.0
1  0.799984  0.399996  0.749981  0.599988  0.699993  0.466664           0.0
2  0.399992  0.333328  0.399992  0.249997  0.399996  0.285712           0.0
3  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000           0.0
4  0.399992  0.199998  0.999950  0.666644  0.571420  0.307690           0.0

   first_word_eq  abs_len_diff  mean_len  token_set_ratio  token_sort_ratio  \
0            1.0           2.0      13.0              100                93
1            1.0           5.0      12.5               86                63
2            1.0           4.0      12.0               63                63
3            0.0           2.0      12.0               28                24
4            1.0           6.0      10.0               67                47

   fuzz_ratio  fuzz_partial_ratio  longest_substr_ratio
0          93                 100              0.982759
1          66                  75              0.596154
2          43                  47              0.166667
3           9                  14              0.039216
4          35                  56              0.175000
```

[30]:
```
df2.head()
```

[30]:
```
   freq_qid1  freq_qid2  q1len  q2len  q1_n_words  q2_n_words  word_Common  \
0          1          1     66     57          14          12         10.0
1          4          1     51     88           8          13          4.0
2          1          1     73     59          14          10          4.0
3          1          1     50     65          11           9          0.0
4          3          1     76     39          13           7          2.0

   word_Total  word_share  freq_q1+q2  freq_q1-q2
0        23.0    0.434783           2           0
1        20.0    0.200000           5           3
2        24.0    0.166667           2           0
3        19.0    0.000000           2           0
4        20.0    0.100000           4           2
```

[31]:
```
df3.head()
```

[31]:
```
   id
0   0
1   1
2   2
```

```
3   3
4   4
```

[32]:
```
df1.shape, df2.shape, df3.shape
```

[32]:
```
((404290, 15), (404290, 11), (100000, 1))
```

[33]:
```
from scipy import sparse
```

[34]:
```
feature_train_df_1 = sparse.csr_matrix(df1[0:train_len])#.to_sparse())
feature_test_df_1 = sparse.csr_matrix(df1[train_len:train_len+test_len])#.
 ↪to_sparse()
feature_train_df_2 = sparse.csr_matrix(df2[0:train_len])#.to_sparse()
feature_test_df_2 = sparse.csr_matrix(df2[train_len:train_len+test_len])#.
 ↪to_sparse()
```

[35]:
```
final_train = hstack((feature_train_df_1, feature_train_df_2, x_train_ques))
final_test = hstack((feature_test_df_1, feature_test_df_2, x_test_ques))
print(final_train.shape, final_test.shape)
```

```
(80000, 950648) (20000, 950648)
```

[36]:
```
print("Number of features in nlp data:", feature_train_df_1.shape[1])
print("Number of features in preprocessed data :", feature_train_df_2.shape[1])
print("Number of features in question1 data :", q1_train_data_vector.shape[1])
print("Number of features in question2 data :", q2_train_data_vector.shape[1])
print("Number of features in final data  :", final_train.shape[1])
```

```
Number of features in nlp data: 15
Number of features in preprocessed data : 11
Number of features in question1 data : 475311
Number of features in question2 data : 475311
Number of features in final data  : 950648
```

[38]:
```
# storing the final features to pkl file
import pickle
dir_path = '.'
if not os.path.isfile(os.path.join(dir_path, 'final_features_tfidf.pkl')):
    with open(os.path.join(dir_path, 'final_features_tfidf.pkl'), 'wb') as f:
        final_data = {}
        final_data['final_train'] = final_train
        final_data['final_test'] = final_test
        final_data['y_train'] = y_train
        final_data['y_test'] = y_test
        pickle.dump(final_data, f)
```

[39]:
```
# restoring final features from pkl file
import pickle
if os.path.isfile(os.path.join(dir_path, 'final_features_tfidf.pkl')):
    with open(os.path.join(dir_path, 'final_features_tfidf.pkl'), 'rb') as f:
```

```
        final_data = pickle.load(f)
final_data.keys()
```

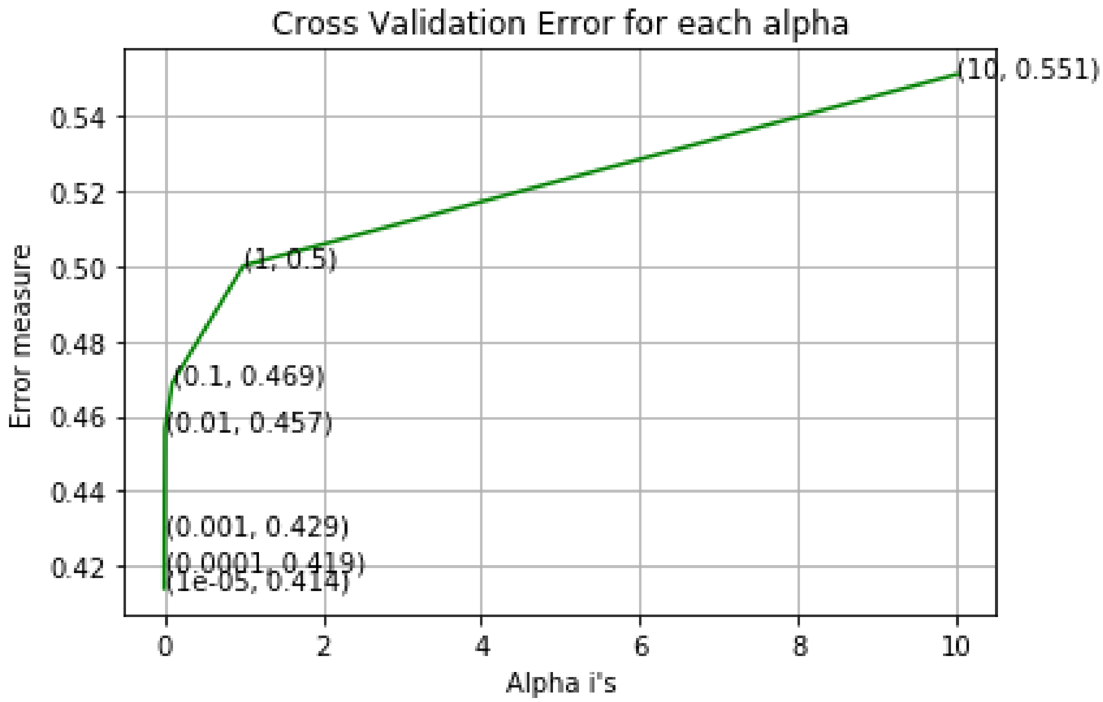
[39]:
```
dict_keys(['final_train', 'final_test', 'y_train', 'y_test'])
```

5.1.2 Logistic Regression (included hyperparameter tuning) with TFIDF

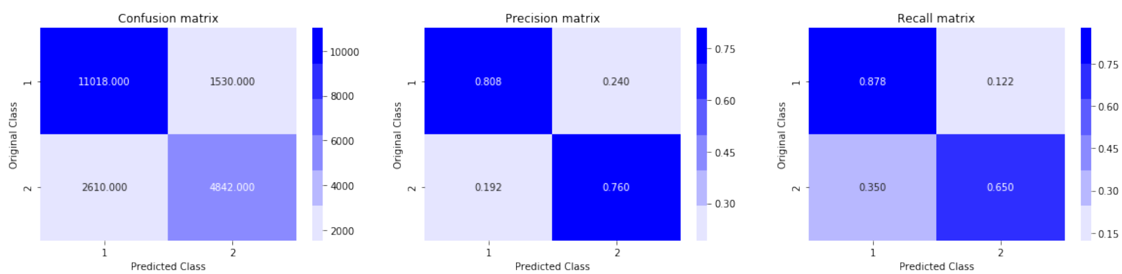
[42]:
```
start = dt.datetime.now()
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/
↪generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss=hinge, penalty=l2, alpha=0.0001, l1_ratio=0.15,␣
↪fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None,␣
↪learning_rate=optimal, eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, ])        Fit linear model with␣
↪Stochastic Gradient Descent.
# predict(X)        Predict class labels for samples in X.

#-------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42)
    clf.fit(final_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(final_train, y_train)
    predict_y = sig_clf.predict_proba(final_test)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_,␣
↪eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test,␣
↪predict_y, labels=clf.classes_, eps=1e-15))

fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
```

```
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='log',␣
 ↪random_state=42)
clf.fit(final_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(final_train, y_train)

predict_y = sig_clf.predict_proba(final_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:
 ↪",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(final_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:
 ↪",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
print('Total time taken to run this cell: ', dt.datetime.now()-start)
```

```
For values of alpha =  1e-05 The log loss is: 0.4140181065549573
For values of alpha =  0.0001 The log loss is: 0.4193929692578037
For values of alpha =  0.001 The log loss is: 0.4286001292713021
For values of alpha =  0.01 The log loss is: 0.4566171682132662
For values of alpha =  0.1 The log loss is: 0.46877360638703686
For values of alpha =  1 The log loss is: 0.5001071999997878
For values of alpha =  10 The log loss is: 0.5510571434546174
```




```
For values of best alpha =  1e-05 The train log loss is: 0.4024544707546233
For values of best alpha =  1e-05 The test log loss is: 0.4140181065549573
Total number of data points : 20000
```




```
Total time taken to run this cell:  0:03:30.543180
```

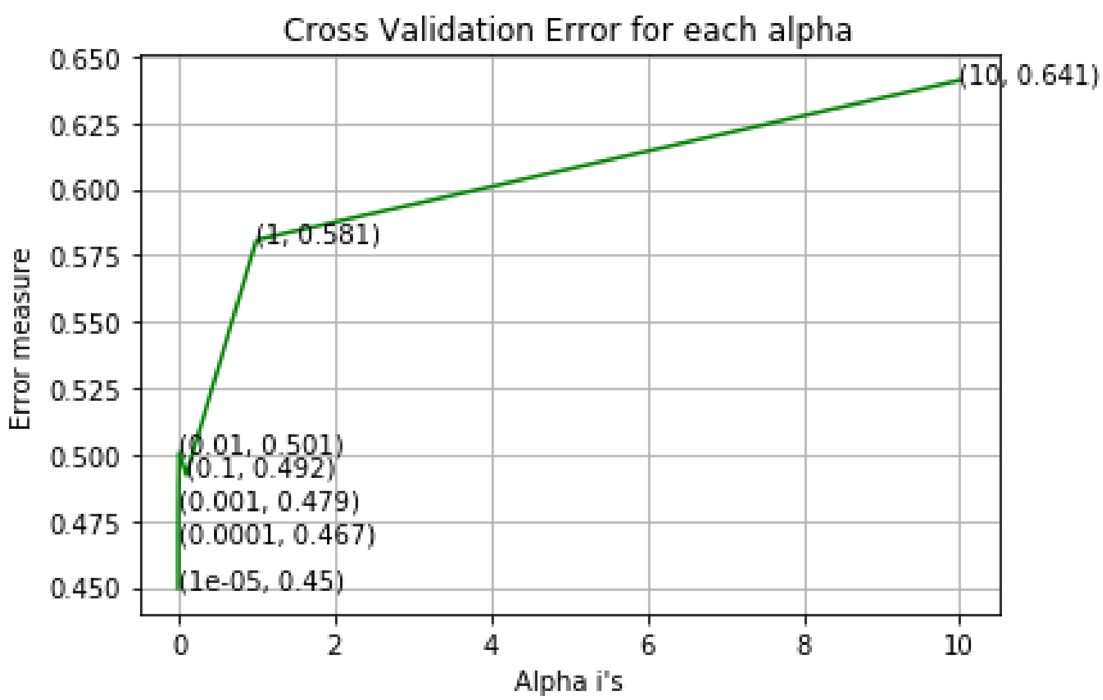
5.1.3 Linear SVM (included hyperparameter tuning) with TFIDF

[43]:
```
start = dt.datetime.now()
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/
↪generated/sklearn.linear_model.SGDClassifier.html
```

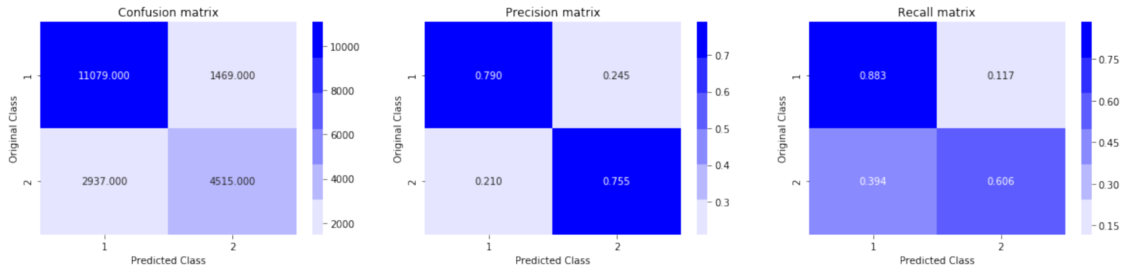
```
# ------------------------------
# default parameters
# SGDClassifier(loss=hinge, penalty=l2, alpha=0.0001, l1_ratio=0.15,␣
↪fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None,␣
↪learning_rate=optimal, eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, ])       Fit linear model with␣
↪Stochastic Gradient Descent.
# predict(X)       Predict class labels for samples in X.

#-------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l1', loss='hinge', random_state=42)
    clf.fit(final_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(final_train, y_train)
    predict_y = sig_clf.predict_proba(final_test)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_,␣
↪eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test,␣
↪predict_y, labels=clf.classes_, eps=1e-15))

fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l1', loss='hinge',␣
↪random_state=42)
clf.fit(final_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
```

```
sig_clf.fit(final_train, y_train)

predict_y = sig_clf.predict_proba(final_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:
 ↪",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(final_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:
 ↪",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
print('Total time taken to run this cell: ', dt.datetime.now()-start)
```

```
For values of alpha =  1e-05 The log loss is: 0.44965497921483527
For values of alpha =  0.0001 The log loss is: 0.4669603586163743
For values of alpha =  0.001 The log loss is: 0.4794782794453354
For values of alpha =  0.01 The log loss is: 0.5008481434442639
For values of alpha =  0.1 The log loss is: 0.49218767296161897
For values of alpha =  1 The log loss is: 0.580802468973458
For values of alpha =  10 The log loss is: 0.6408841734577491
```




```
For values of best alpha =  1e-05 The train log loss is: 0.43964101821105994
For values of best alpha =  1e-05 The test log loss is: 0.44965497921483527
Total number of data points : 20000
```




```
Total time taken to run this cell:  0:13:20.618174
```

5.2 Hyperparameter tune XgBoost using RandomSearch to reduce the log-loss. Used Same DataSet i.e. TFIDFW2V

5.2.1 Preprocess TFIDFW2V Data i.e Fit train data then transform test data on it

[3]:
```
# avoid decoding problems
df = pd.read_csv("train.csv")

# encode questions to unicode
# https://stackoverflow.com/a/6812069
# ----------------- python 2 ---------------------
# df['question1'] = df['question1'].apply(lambda x: unicode(str(x),"utf-8"))
# df['question2'] = df['question2'].apply(lambda x: unicode(str(x),"utf-8"))
# ----------------- python 3 ---------------------
df['question1'] = df['question1'].apply(lambda x: str(x))
df['question2'] = df['question2'].apply(lambda x: str(x))
```

[4]:
```
df.head()
```

[4]:
```
   id  qid1  qid2                                          question1  \
0   0     1     2  What is the step by step guide to invest in sh...
1   1     3     4  What is the story of Kohinoor (Koh-i-Noor) Dia...
2   2     5     6  How can I increase the speed of my internet co...
3   3     7     8  Why am I mentally very lonely? How can I solve...
4   4     9    10  Which one dissolve in water quikly sugar, salt...

                                           question2  is_duplicate
0  What is the step by step guide to invest in sh...             0
1  What would happen if the Indian government sto...             0
2  How can Internet speed be increased by hacking...             0
3  Find the remainder when [math]23^{24}[/math] i...             0
4            Which fish would survive in salt water?             0
```

[5]:
```
df.shape
```

[5]:
```
(404290, 6)
```

[6]:
```
# define train and test length (100000 = 80000+20000)
train_len = 80000
```

```
test_len = 20000
```

[7]:
```
# prepare test and train data
q1_train_data = df['question1'][0:train_len].copy()
q1_test_data = df['question1'][train_len:train_len+test_len].copy()
q2_train_data = df['question2'][0:train_len].copy()
q2_test_data = df['question2'][train_len:train_len+test_len].copy()
```

[8]:
```
q1_train_data.head()
```

[8]:
```
0    What is the step by step guide to invest in sh...
1    What is the story of Kohinoor (Koh-i-Noor) Dia...
2    How can I increase the speed of my internet co...
3    Why am I mentally very lonely? How can I solve...
4    Which one dissolve in water quikly sugar, salt...
Name: question1, dtype: object
```

[9]:
```
q1_test_data.head()
```

[9]:
```
80000        How do I recover deleted files in an Android?
80001                   What are some good start up ideas?
80002    What reason does philosophy give for our exist...
80003    What are the differences between a sociopath a...
80004    How do I talk to my parents to give me more fr...
Name: question1, dtype: object
```

[10]:
```
q2_train_data.head()
```

[10]:
```
0    What is the step by step guide to invest in sh...
1    What would happen if the Indian government sto...
2    How can Internet speed be increased by hacking...
3    Find the remainder when [math]23^{24}[/math] i...
4              Which fish would survive in salt water?
Name: question2, dtype: object
```

[11]:
```
q2_test_data.head()
```

[11]:
```
80000    How do I recover deleted files on an Android p...
80001                  What is the best start up to start?
80002    How much income can I generate by selling an e...
80003    What are the trait differences of a sociopath ...
80004           How do I start talking more to my parents?
Name: question2, dtype: object
```

[12]:
```
# merge texts
questions = list(q1_train_data) + list(q2_train_data)
```

[13]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
# merge texts
# questions = list(df['question1']) + list(df['question2'])
```

```
tfidf = TfidfVectorizer(lowercase=False, )
tfidf.fit(questions)

# dict key:word and value:tf-idf score
word2tfidf = dict(zip(tfidf.get_feature_names(), tfidf.idf_))
```

- After we find TF-IDF scores, we convert each question to a weighted average of word2vec vectors by these scores.
- here we use a pre-trained GLOVE model which comes free with “Spacy”. https://spacy.io/usage/vectors-similarity
- It is trained on Wikipedia and therefore, it is stronger in terms of word semantics.

[14]:
```
import spacy
# en_vectors_web_lg, which includes over 1 million unique vectors.
nlp = spacy.load('en_core_web_lg')#en_core_web_sm
```

[16]:
```
from tqdm import tqdm
```

[17]:
```
vecs1 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qu1 in tqdm(list(q1_train_data.values.tolist())):
    doc1 = nlp(qu1)
    # 300 is the number of dimensions of vectors
    mean_vec1 = np.zeros([len(doc1), len(doc1[0].vector)])
    for word1 in doc1:
        # word2vec
        vec1 = word1.vector
        # fetch df score
        try:
            idf = word2tfidf[str(word1)]
        except:
            idf = 0
        # compute final vec
        mean_vec1 += vec1 * idf
    mean_vec1 = mean_vec1.mean(axis=0)
    vecs1.append(mean_vec1)
q1_train_data_vector = list(vecs1)
```

```
100%|| 80000/80000 [09:55<00:00, 134.30it/s]
```

[18]:
```
vecs2 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qu2 in tqdm(list(q1_test_data.values.tolist())):
    doc2 = nlp(qu2)
    mean_vec2 = np.zeros([len(doc2), len(doc2[0].vector)])
    for word2 in doc2:
```

```
        # word2vec
        vec2 = word2.vector
        # fetch df score
        try:
            idf = word2tfidf[str(word2)]
        except:
            #print word
            idf = 0
        # compute final vec
        mean_vec2 += vec2 * idf
    mean_vec2 = mean_vec2.mean(axis=0)
    vecs2.append(mean_vec2)
q1_test_data_vector = list(vecs2)
```

```
100%|| 20000/20000 [02:06<00:00, 157.52it/s]
```

[19]:
```
vecs3 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qu3 in tqdm(list(q2_train_data.values.tolist())):
    doc3 = nlp(qu3)
    mean_vec3 = np.zeros([len(doc3), len(doc3[0].vector)])
    for word3 in doc3:
        # word2vec
        vec3 = word3.vector
        # fetch df score
        try:
            idf = word2tfidf[str(word3)]
        except:
            #print word
            idf = 0
        # compute final vec
        mean_vec3 += vec3 * idf
    mean_vec3 = mean_vec3.mean(axis=0)
    vecs3.append(mean_vec3)
q2_train_data_vector = list(vecs3)
```

```
100%|| 80000/80000 [08:20<00:00, 159.75it/s]
```

[20]:
```
vecs4 = []
# https://github.com/noamraph/tqdm
# tqdm is used to print the progress bar
for qu4 in tqdm(list(q2_test_data.values.tolist())):
    doc4 = nlp(qu4)
    mean_vec4 = np.zeros([len(doc4), len(doc4[0].vector)])
    for word4 in doc4:
        # word2vec
```

```
        vec4 = word4.vector
        # fetch df score
        try:
            idf = word2tfidf[str(word4)]
        except:
            #print word
            idf = 0
        # compute final vec
        mean_vec4 += vec4 * idf
    mean_vec4 = mean_vec4.mean(axis=0)
    vecs4.append(mean_vec4)
q2_test_data_vector = list(vecs4)
```

```
100%|| 20000/20000 [02:07<00:00, 156.43it/s]
```

[ ]:
```
# q1_train_data_vector = tfidf.transform(q1_train_data.values.tolist())
# q1_test_data_vector = tfidf.transform(q1_test_data.values.tolist())
# q2_train_data_vector = tfidf.transform(q2_train_data.values.tolist())
# q2_test_data_vector = tfidf.transform(q2_test_data.values.tolist())
```

[22]:
```
print("Shape of Question1 Data:", len(q1_train_data_vector),␣
 ↪len(q1_test_data_vector))
print("Shape of Question2 Data:", len(q2_train_data_vector),␣
 ↪len(q2_test_data_vector))
```

```
Shape of Question1 Data: 80000 20000
Shape of Question2 Data: 80000 20000
```

[32]:
```
q1_train_data_vector_real = q1_train_data_vector
q1_test_data_vector_real = q1_test_data_vector
q2_train_data_vector_real = q2_train_data_vector
q2_test_data_vector_real = q2_test_data_vector
```

[33]:
```
q1_train_data_vector_df = pd.DataFrame(q1_train_data_vector_real)
```

[35]:
```
q1_test_data_vector_df = pd.DataFrame(q1_test_data_vector_real)
```

[36]:
```
q2_train_data_vector_df = pd.DataFrame(q2_train_data_vector_real)
```

[37]:
```
q2_test_data_vector_df = pd.DataFrame(q2_test_data_vector_real)
```

[38]:
```
q1_train_data_vector_df.shape, q1_test_data_vector_df.shape,␣
 ↪q2_train_data_vector_df.shape, q2_test_data_vector_df.shape
```

[38]:
```
((80000, 300), (20000, 300), (80000, 300), (20000, 300))
```

[39]:
```
from scipy.sparse import hstack
```

[41]:
```
from scipy import sparse
```

[45]:
```
x_train_ques_1 = sparse.csr_matrix(q1_train_data_vector_df)
x_test_ques_1 = sparse.csr_matrix(q1_test_data_vector_df)
x_train_ques_2 = sparse.csr_matrix(q2_train_data_vector_df)
x_test_ques_2 = sparse.csr_matrix(q2_test_data_vector_df)
```

[46]:
```
# a
```

[47]:
```
# x_train_ques = hstack([q1_train_data_vector_df, q2_train_data_vector_df])
# x_test_ques = hstack([q1_test_data_vector_df, q2_test_data_vector_df])
```

[48]:
```
x_train_ques_1.shape, x_test_ques_1.shape, x_train_ques_2.shape, x_test_ques_2.
 ↪shape
```

[48]:
```
((80000, 300), (20000, 300), (80000, 300), (20000, 300))
```

[49]:
```
df = df.head(100000)
```

[50]:
```
df.columns
```

[50]:
```
Index(['id', 'qid1', 'qid2', 'question1', 'question2', 'is_duplicate'],
dtype='object')
```

[51]:
```
y_train = df['is_duplicate'][0:train_len].values.tolist()
y_test = df['is_duplicate'][train_len:train_len+test_len].values.tolist()
```

[52]:
```
len(y_train), len(y_test)
```

[52]:
```
(80000, 20000)
```

[53]:
```
y_train[0:10]
```

[53]:
```
[0, 0, 0, 0, 0, 1, 0, 1, 0, 0]
```

[54]:
```
y_test[0:10]
```

[54]:
```
[1, 1, 0, 1, 0, 0, 1, 0, 0, 1]
```

[55]:
```
a = df['is_duplicate'][80000:5+80000].values.tolist()
a
```

[55]:
```
[1, 1, 0, 1, 0]
```

[56]:
```
#prepro_features_train.csv (Simple Preprocessing Feartures)
#nlp_features_train.csv (NLP Features)
if os.path.isfile('nlp_features_train.csv'):
    dfnlp = pd.read_csv("nlp_features_train.csv",encoding='latin-1')
else:
    print("download nlp_features_train.csv from drive or run previous notebook")

if os.path.isfile('df_fe_without_preprocessing_train.csv'):
    dfppro = pd.read_csv("df_fe_without_preprocessing_train.
 ↪csv",encoding='latin-1')
else:
    print("download df_fe_without_preprocessing_train.csv from drive or run␣
 ↪previous notebook")
```

[57]:
```
df1 = dfnlp.drop(['qid1','qid2','question1','question2'],axis=1)
df2 = dfppro.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
df3 = df.drop(['qid1','qid2','question1','question2','is_duplicate'],axis=1)
# df3_q1 = pd.DataFrame(df3.q1_feats_m.values.tolist(), index= df3.index)
# df3_q2 = pd.DataFrame(df3.q2_feats_m.values.tolist(), index= df3.index)

df1.columns, df2.columns, df3.columns
```

[57]:
```
(Index(['id', 'is_duplicate', 'cwc_min', 'cwc_max', 'csc_min', 'csc_max',
        'ctc_min', 'ctc_max', 'last_word_eq', 'first_word_eq', 'abs_len_diff',
        'mean_len', 'token_set_ratio', 'token_sort_ratio', 'fuzz_ratio',
        'fuzz_partial_ratio', 'longest_substr_ratio'],
       dtype='object'),
 Index(['id', 'freq_qid1', 'freq_qid2', 'q1len', 'q2len', 'q1_n_words',
        'q2_n_words', 'word_Common', 'word_Total', 'word_share', 'freq_q1+q2',
        'freq_q1-q2'],
       dtype='object'),
 Index(['id'], dtype='object'))
```

[58]:
```
df1 = df1.drop(['id', 'is_duplicate'], axis=1)
df2 = df2.drop(['id'], axis=1)

df1.columns, df2.columns
```

[58]:
```
(Index(['cwc_min', 'cwc_max', 'csc_min', 'csc_max', 'ctc_min', 'ctc_max',
        'last_word_eq', 'first_word_eq', 'abs_len_diff', 'mean_len',
        'token_set_ratio', 'token_sort_ratio', 'fuzz_ratio',
        'fuzz_partial_ratio', 'longest_substr_ratio'],
       dtype='object'),
 Index(['freq_qid1', 'freq_qid2', 'q1len', 'q2len', 'q1_n_words', 'q2_n_words',
        'word_Common', 'word_Total', 'word_share', 'freq_q1+q2', 'freq_q1-q2'],
       dtype='object'))
```

[59]:
```
df1.head()
```

[59]:
```
    cwc_min   cwc_max   csc_min   csc_max   ctc_min   ctc_max  last_word_eq  \
0  0.999980  0.833319  0.999983  0.999983  0.916659  0.785709           0.0
1  0.799984  0.399996  0.749981  0.599988  0.699993  0.466664           0.0
2  0.399992  0.333328  0.399992  0.249997  0.399996  0.285712           0.0
3  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000           0.0
4  0.399992  0.199998  0.999950  0.666644  0.571420  0.307690           0.0

   first_word_eq  abs_len_diff  mean_len  token_set_ratio  token_sort_ratio  \
0            1.0           2.0      13.0              100                93
1            1.0           5.0      12.5               86                63
2            1.0           4.0      12.0               63                63
3            0.0           2.0      12.0               28                24
4            1.0           6.0      10.0               67                47
```

```
   fuzz_ratio  fuzz_partial_ratio  longest_substr_ratio
0          93                 100              0.982759
1          66                  75              0.596154
2          43                  47              0.166667
3           9                  14              0.039216
4          35                  56              0.175000
```

[60]:
```
df2.head()
```

[60]:
```
   freq_qid1  freq_qid2  q1len  q2len  q1_n_words  q2_n_words  word_Common  \
0          1          1     66     57          14          12         10.0
1          4          1     51     88           8          13          4.0
2          1          1     73     59          14          10          4.0
3          1          1     50     65          11           9          0.0
4          3          1     76     39          13           7          2.0

   word_Total  word_share  freq_q1+q2  freq_q1-q2
0        23.0    0.434783           2           0
1        20.0    0.200000           5           3
2        24.0    0.166667           2           0
3        19.0    0.000000           2           0
4        20.0    0.100000           4           2
```

[61]:
```
df3.head()
```

[61]:
```
   id
0   0
1   1
2   2
3   3
4   4
```

[62]:
```
df1.shape, df2.shape, df3.shape
```

[62]:
```
((404290, 15), (404290, 11), (100000, 1))
```

[63]:
```
from scipy import sparse
```

[64]:
```
feature_train_df_1 = sparse.csr_matrix(df1[0:train_len])#.to_sparse())
feature_test_df_1 = sparse.csr_matrix(df1[train_len:train_len+test_len])#.
↪to_sparse()
feature_train_df_2 = sparse.csr_matrix(df2[0:train_len])#.to_sparse()
feature_test_df_2 = sparse.csr_matrix(df2[train_len:train_len+test_len])#.
↪to_sparse()
```

[66]:
```
final_train = hstack((feature_train_df_1, feature_train_df_2, x_train_ques_1,␣
↪x_train_ques_2))
final_test = hstack((feature_test_df_1, feature_test_df_2, x_test_ques_1,␣
↪x_test_ques_2))
print(final_train.shape, final_test.shape)
```

```
(80000, 626) (20000, 626)
```

[69]:
```
print("Number of features in nlp data:", feature_train_df_1.shape[1])
print("Number of features in preprocessed data :", feature_train_df_2.shape[1])
print("Number of features in question1 data :", len(q1_train_data_vector[0]))
print("Number of features in question2 data :", len(q2_train_data_vector[0]))
print("Number of features in final data  :", final_train.shape[1])
```

```
Number of features in nlp data: 15
Number of features in preprocessed data : 11
Number of features in question1 data : 300
Number of features in question2 data : 300
Number of features in final data  : 626
```

[70]:
```
# storing the final features to pkl file
import pickle
dir_path = '.'
if not os.path.isfile(os.path.join(dir_path, 'final_features_tfidfw2v.pkl')):
    with open(os.path.join(dir_path, 'final_features_tfidfw2v.pkl'), 'wb') as f:
        final_data = {}
        final_data['final_train'] = final_train
        final_data['final_test'] = final_test
        final_data['y_train'] = y_train
        final_data['y_test'] = y_test
        pickle.dump(final_data, f)
```

[5]:
```
# restoring final features from pkl file
import pickle
dir_path = '.'
if os.path.isfile(os.path.join(dir_path, 'final_features_tfidfw2v.pkl')):
    with open(os.path.join(dir_path, 'final_features_tfidfw2v.pkl'), 'rb') as f:
        final_data = pickle.load(f)
final_data.keys()
```

[5]:
```
dict_keys(['final_train', 'final_test', 'y_train', 'y_test'])
```

[7]:
```
final_train = final_data['final_train']
final_test = final_data['final_test']
y_train = final_data['y_train']
y_test = final_data['y_test']
```

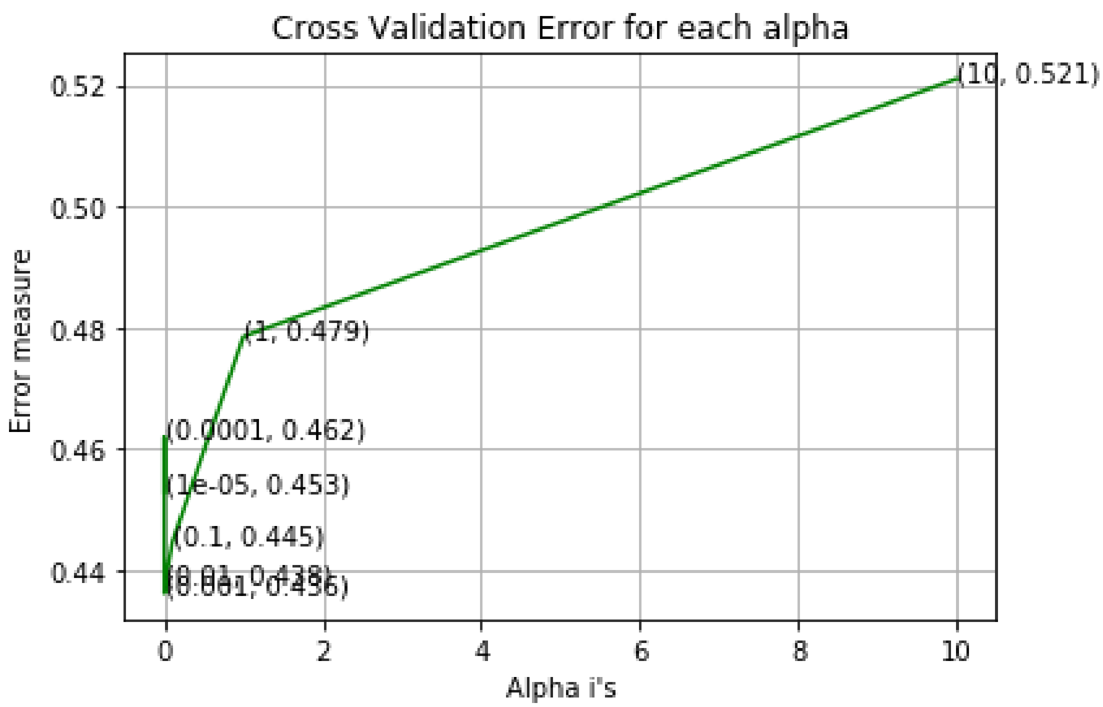
5.2.2 Logistic Regression (included hyperparameter tuning) with TFIDFW2V

[75]:
```
start = dt.datetime.now()
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/
 ↪generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss=hinge, penalty=l2, alpha=0.0001, l1_ratio=0.15,␣
 ↪fit_intercept=True, max_iter=None, tol=None,
```

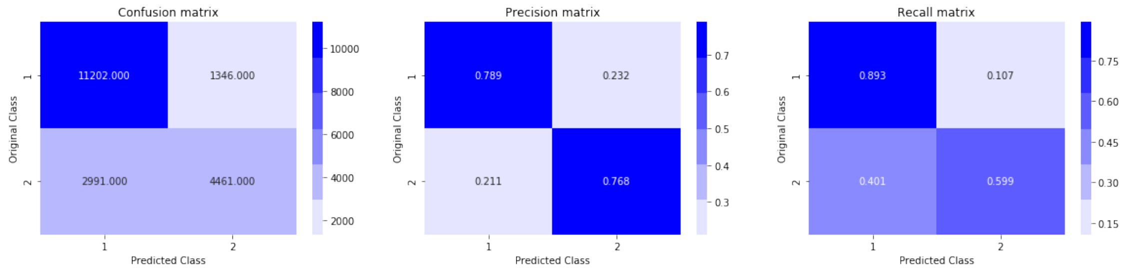
```
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None,␣
↪learning_rate=optimal, eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, ])       Fit linear model with␣
↪Stochastic Gradient Descent.
# predict(X)        Predict class labels for samples in X.

#-------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l2', loss='log', random_state=42)
    clf.fit(final_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(final_train, y_train)
    predict_y = sig_clf.predict_proba(final_test)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_,␣
↪eps=1e-15))
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test,␣
↪predict_y, labels=clf.classes_, eps=1e-15))

fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l2', loss='log',␣
↪random_state=42)
clf.fit(final_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(final_train, y_train)

predict_y = sig_clf.predict_proba(final_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:
↪",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
```

```
predict_y = sig_clf.predict_proba(final_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:
 ↪",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
print('Total time taken to run this cell: ', dt.datetime.now()-start)
```

```
For values of alpha =  1e-05 The log loss is: 0.4528222254310883
For values of alpha =  0.0001 The log loss is: 0.46204032650544213
For values of alpha =  0.001 The log loss is: 0.436159127992777
For values of alpha =  0.01 The log loss is: 0.43792215378677074
For values of alpha =  0.1 The log loss is: 0.4445686280511855
For values of alpha =  1 The log loss is: 0.4785482845783462
For values of alpha =  10 The log loss is: 0.5210199369936789
```




```
For values of best alpha =  0.001 The train log loss is: 0.42976504261399623
For values of best alpha =  0.001 The test log loss is: 0.436159127992777
Total number of data points : 20000
```



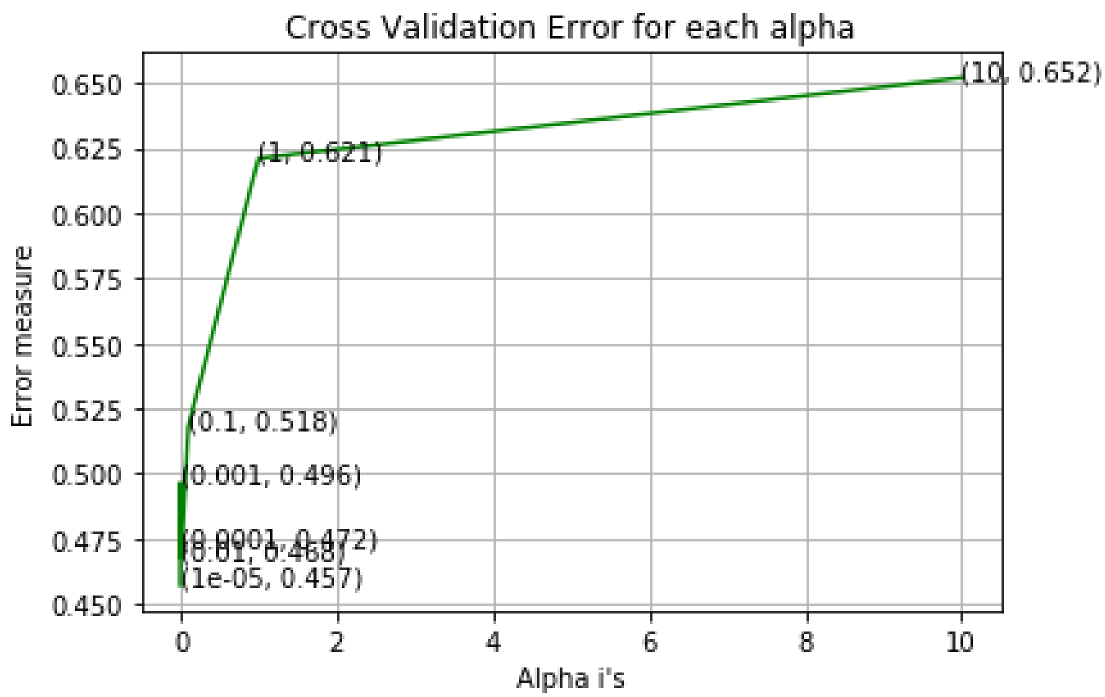

```
Total time taken to run this cell:  0:57:36.911350
```

5.2.3 Linear SVM (included hyperparameter tuning) with TFIDFW2V

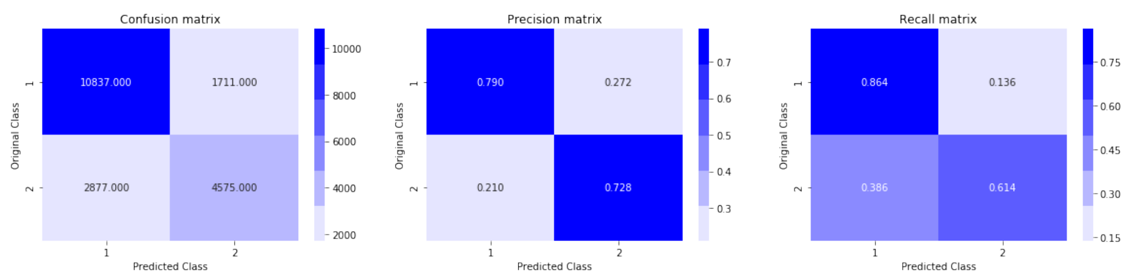
[9]:
```
start = dt.datetime.now()
alpha = [10 ** x for x in range(-5, 2)] # hyperparam for SGD classifier.

# read more about SGDClassifier() at http://scikit-learn.org/stable/modules/
↪generated/sklearn.linear_model.SGDClassifier.html
# ------------------------------
# default parameters
# SGDClassifier(loss=hinge, penalty=l2, alpha=0.0001, l1_ratio=0.15,␣
↪fit_intercept=True, max_iter=None, tol=None,
# shuffle=True, verbose=0, epsilon=0.1, n_jobs=1, random_state=None,␣
↪learning_rate=optimal, eta0=0.0, power_t=0.5,
# class_weight=None, warm_start=False, average=False, n_iter=None)

# some of methods
# fit(X, y[, coef_init, intercept_init, ])       Fit linear model with␣
↪Stochastic Gradient Descent.
# predict(X)        Predict class labels for samples in X.

#-------------------------------
# video link:
#------------------------------


log_error_array=[]
for i in alpha:
    clf = SGDClassifier(alpha=i, penalty='l1', loss='hinge', random_state=42)
    clf.fit(final_train, y_train)
    sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
    sig_clf.fit(final_train, y_train)
    predict_y = sig_clf.predict_proba(final_test)
    log_error_array.append(log_loss(y_test, predict_y, labels=clf.classes_,␣
↪eps=1e-15))
```

```
    print('For values of alpha = ', i, "The log loss is:",log_loss(y_test,␣
↪predict_y, labels=clf.classes_, eps=1e-15))

fig, ax = plt.subplots()
ax.plot(alpha, log_error_array,c='g')
for i, txt in enumerate(np.round(log_error_array,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error_array[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()


best_alpha = np.argmin(log_error_array)
clf = SGDClassifier(alpha=alpha[best_alpha], penalty='l1', loss='hinge',␣
↪random_state=42)
clf.fit(final_train, y_train)
sig_clf = CalibratedClassifierCV(clf, method="sigmoid")
sig_clf.fit(final_train, y_train)

predict_y = sig_clf.predict_proba(final_train)
print('For values of best alpha = ', alpha[best_alpha], "The train log loss is:
↪",log_loss(y_train, predict_y, labels=clf.classes_, eps=1e-15))
predict_y = sig_clf.predict_proba(final_test)
print('For values of best alpha = ', alpha[best_alpha], "The test log loss is:
↪",log_loss(y_test, predict_y, labels=clf.classes_, eps=1e-15))
predicted_y =np.argmax(predict_y,axis=1)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
print('Total time taken to run this cell: ', dt.datetime.now()-start)
```

```
For values of alpha =  1e-05 The log loss is: 0.4570607375982754
For values of alpha =  0.0001 The log loss is: 0.4717054966776061
For values of alpha =  0.001 The log loss is: 0.496387355416979
For values of alpha =  0.01 The log loss is: 0.4675490800272124
For values of alpha =  0.1 The log loss is: 0.5177872827509853
For values of alpha =  1 The log loss is: 0.6210757744330847
For values of alpha =  10 The log loss is: 0.652027518450825
```




```
For values of best alpha =  1e-05 The train log loss is: 0.44657748860295596
For values of best alpha =  1e-05 The test log loss is: 0.4570607375982754
Total number of data points : 20000
```




```
Total time taken to run this cell:  1:43:36.017388
```

5.2.4 Xgboost (included hyperparameter tuning) with TFIDFW2V

[10]:
```
start = dt.datetime.now()
import xgboost as xgb
params = {}
params['objective'] = 'binary:logistic'
params['eval_metric'] = 'logloss'
params['eta'] = 0.02
```

```
params['max_depth'] = 4

d_train = xgb.DMatrix(final_train, label=y_train)
d_test = xgb.DMatrix(final_test, label=y_test)

watchlist = [(d_train, 'train'), (d_test, 'valid')]

bst = xgb.train(params, d_train, 400, watchlist, early_stopping_rounds=20,␣
 ↪verbose_eval=10)

xgdmat = xgb.DMatrix(final_train,y_train)
predict_y = bst.predict(d_test)
print("The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_,␣
 ↪eps=1e-15))
```

```
[0]     train-logloss:0.68482   valid-logloss:0.684945
Multiple eval metrics have been passed: 'valid-logloss' will be used for early
stopping.

Will train until valid-logloss hasn't improved in 20 rounds.
[10]    train-logloss:0.616184  valid-logloss:0.61754
[20]    train-logloss:0.565189  valid-logloss:0.567302
[30]    train-logloss:0.527267  valid-logloss:0.529908
[40]    train-logloss:0.497602  valid-logloss:0.500854
[50]    train-logloss:0.474749  valid-logloss:0.478433
[60]    train-logloss:0.456418  valid-logloss:0.460625
[70]    train-logloss:0.441652  valid-logloss:0.446347
[80]    train-logloss:0.429682  valid-logloss:0.434825
[90]    train-logloss:0.41981   valid-logloss:0.425401
[100]   train-logloss:0.411667  valid-logloss:0.417563
[110]   train-logloss:0.404821  valid-logloss:0.411104
[120]   train-logloss:0.399146  valid-logloss:0.405632
[130]   train-logloss:0.394256  valid-logloss:0.40095
[140]   train-logloss:0.389993  valid-logloss:0.396995
[150]   train-logloss:0.386207  valid-logloss:0.393519
[160]   train-logloss:0.383222  valid-logloss:0.390716
[170]   train-logloss:0.380503  valid-logloss:0.388221
[180]   train-logloss:0.37793   valid-logloss:0.385869
[190]   train-logloss:0.375643  valid-logloss:0.383712
[200]   train-logloss:0.373435  valid-logloss:0.381613
[210]   train-logloss:0.371441  valid-logloss:0.379848
[220]   train-logloss:0.36955   valid-logloss:0.378155
[230]   train-logloss:0.367856  valid-logloss:0.376619
[240]   train-logloss:0.366089  valid-logloss:0.375051
[250]   train-logloss:0.364097  valid-logloss:0.373283
[260]   train-logloss:0.362516  valid-logloss:0.371899
[270]   train-logloss:0.360787  valid-logloss:0.370455
```

```
[280]   train-logloss:0.359296  valid-logloss:0.369227
[290]   train-logloss:0.357918  valid-logloss:0.3681
[300]   train-logloss:0.356712  valid-logloss:0.367195
[310]   train-logloss:0.355428  valid-logloss:0.366173
[320]   train-logloss:0.354066  valid-logloss:0.365144
[330]   train-logloss:0.352899  valid-logloss:0.36429
[340]   train-logloss:0.351755  valid-logloss:0.363421
[350]   train-logloss:0.350535  valid-logloss:0.362585
[360]   train-logloss:0.349495  valid-logloss:0.361887
[370]   train-logloss:0.348363  valid-logloss:0.36107
[380]   train-logloss:0.347329  valid-logloss:0.360361
[390]   train-logloss:0.346248  valid-logloss:0.359556
[399]   train-logloss:0.345386  valid-logloss:0.358948
The test log loss is: 0.35894935881944257
```

[11]:
```
from sklearn.model_selection import RandomizedSearchCV
```

[12]:
```
import xgboost as xgb
```

5.2.5 Hyperparameter

[16]:
```
# max_depth=[int(x) for x in np.linspace(start=2, stop=10, num=9)]
# n_estimators=[int(x) for x in np.linspace(start=50, stop=300, num=6)]
# learning_rate=[float(x) for x in np.linspace(start=0.1, stop=0.9, num=9)]
# booster="gbtree", "gblinear",

# random_grid = {
#     'max_depth' : max_depth,
#     'n_estimators' : n_estimators,
#     'learning_rate' : learning_rate,
#     'booster' : booster
# }

# random_grid={
#     'learning_rate':[0.01,0.03,0.05,0.1,0.15,0.2],
#     'n_estimators':[100,200,500,1000,2000],
#     'max_depth':[2,3,4,5],
#     'colsample_bytree':[0.1,0.3,0.5,1],
#     'subsample':[0.1,0.3,0.5,1]
# }

# As per applied AI instructor I will optimize only n_estimators and max_depth␣
↪upto 10
random_grid={
    'n_estimators':[100,200,500,1000,2000],
    'max_depth':[2,3,4,5,6,7,8,9,10],
}

random_grid
```

[16]:
```
{'n_estimators': [100, 200, 500, 1000, 2000],
 'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]}
```

[17]:
```
# # Use the random grid to search for best hyperparameters
# # First create the base model to tune
# xgb_random = xgb.XGBRegressor(nthread=-1, objective='reg:linear',␣
↪missing=None, seed=8)
# # Random search of parameters, using 3 fold cross validation,
# # search across 100 different combinations, and use all available cores
# xgb_random = RandomizedSearchCV(estimator = xgb_random, param_distributions =␣
↪random_grid, n_iter = 100, cv = 3, verbose=2, random_state=42, n_jobs = -1)
# # Fit the random search model
# xgb_random.fit(x_train, y_train)
# Use the random grid to search for best hyperparameters
# First create the base model to tune
#  class xgboost.XGBRegressor(max_depth=3, learning_rate=0.1, n_estimators=100,␣
↪verbosity=1,
# objective='reg:squarederror', booster='gbtree', tree_method='auto',
# n_jobs=1, gamma=0, min_child_weight=1, max_delta_step=0, subsample=1,
# colsample_bytree=1, colsample_bylevel=1, colsample_bynode=1,
# reg_alpha=0, reg_lambda=1, scale_pos_weight=1, base_score=0.5,
# random_state=0, missing=None, num_parallel_tree=1, importance_type='gain',␣
↪**kwargs)
# xgb_random = xgb.XGBRegressor(n_jobs=-1)#, random_state=15
# xgb_random = xgb.XGBRegressor(nthread=-1, objective='reg:linear',␣
↪missing=None, seed=8)
# initialize XGBClassifier
xgb_random = xgb.XGBClassifier(n_jobs=-1)
# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores
xgb_random = RandomizedSearchCV(estimator = xgb_random, param_distributions =␣
↪random_grid, n_iter = 100, cv = 3, verbose=3, n_jobs = -1)#random_state=15,
# Fit the random search model
xgb_random.fit(final_train,y_train)
```

```
Fitting 3 folds for each of 45 candidates, totalling 135 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  24 tasks      | elapsed: 440.9min
[Parallel(n_jobs=-1)]: Done 120 tasks      | elapsed: 4759.6min
[Parallel(n_jobs=-1)]: Done 135 out of 135 | elapsed: 5991.6min finished
```

[17]:
```
RandomizedSearchCV(cv=3, error_score='raise-deprecating',
                   estimator=XGBClassifier(base_score=0.5, booster='gbtree',
                                           colsample_bylevel=1,
                                           colsample_bynode=1,
                                           colsample_bytree=1, gamma=0,
                                           learning_rate=0.1, max_delta_step=0,
```

```
                                              max_depth=3, min_child_weight=1,
                                              missing=None, n_estimators=100,
                                              n_jobs=-1, nthread=None,
                                              objective='binary:logistic',
                                              random_state=0, reg_alpha=0,
                                              reg_lambda=1, scale_pos_weight=1,
                                              seed=None, silent=None, subsample=1,
                                              verbosity=1),
                        iid='warn', n_iter=100, n_jobs=-1,
                        param_distributions={'max_depth': [2, 3, 4, 5, 6, 7, 8, 9,
                                                           10],
                                             'n_estimators': [100, 200, 500, 1000,
                                                              2000]},
                        pre_dispatch='2*n_jobs', random_state=None, refit=True,
                        return_train_score=False, scoring=None, verbose=3)
```

[18]:
```
# select best params
xgb_random.best_params_
```

[18]:
```
{'n_estimators': 2000, 'max_depth': 7}
```

5.2.6 Run Xgboost using best Hyperparameter

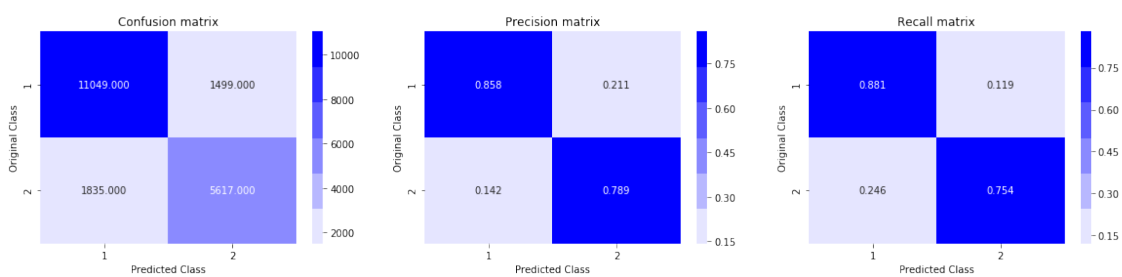
[20]:
```
# {'subsample': 1,
#  'n_estimators': 1000,
#  'max_depth': 5,
#  'learning_rate': 0.05,
#  'colsample_bytree': 0.3}

start = dt.datetime.now()
import xgboost as xgb
params = {}
params['objective'] = 'binary:logistic'
params['eval_metric'] = 'logloss'
# params['subsample'] = 1
params['n_estimators'] = 2000
params['max_depth'] = 7
# params['eta'] = 0.05
# params['colsample_bytree'] = 0.3


# {'learning_rate': [0.01, 0.03, 0.05, 0.1, 0.15, 0.2],
#  'n_estimators': [100, 200, 500, 1000, 2000],
#  'max_depth': [2, 3, 4, 5],
#  'colsample_bytree': [0.1, 0.3, 0.5, 1],
#  'subsample': [0.1, 0.3, 0.5, 1]}

d_train = xgb.DMatrix(final_train, label=y_train)
d_test = xgb.DMatrix(final_test, label=y_test)
```

```
watchlist = [(d_train, 'train'), (d_test, 'valid')]

bst = xgb.train(params, d_train, 400, watchlist, early_stopping_rounds=20,␣
 ↪verbose_eval=10)

xgdmat = xgb.DMatrix(final_train,y_train)
predict_y = bst.predict(d_test)
print("The test log loss is:",log_loss(y_test, predict_y, labels=clf.classes_,␣
 ↪eps=1e-15))
```

```
[0]     train-logloss:0.566011  valid-logloss:0.57037
Multiple eval metrics have been passed: 'valid-logloss' will be used for early
stopping.

Will train until valid-logloss hasn't improved in 20 rounds.
[10]    train-logloss:0.333082  valid-logloss:0.362079
[20]    train-logloss:0.296601  valid-logloss:0.346738
[30]    train-logloss:0.262719  valid-logloss:0.340093
[40]    train-logloss:0.230755  valid-logloss:0.33808
[50]    train-logloss:0.206959  valid-logloss:0.336675
[60]    train-logloss:0.187235  valid-logloss:0.33786
[70]    train-logloss:0.168236  valid-logloss:0.338469
Stopping. Best iteration:
[50]    train-logloss:0.206959  valid-logloss:0.336675

The test log loss is: 0.3384723600838287
```

[21]:
```
predicted_y =np.array(predict_y>0.5,dtype=int)
print("Total number of data points :", len(predicted_y))
plot_confusion_matrix(y_test, predicted_y)
print('Total time taken to run this cell: ', dt.datetime.now()-start)
```

```
Total number of data points : 20000
```




```
Total time taken to run this cell:  0:14:48.470554
```

6. Conclusion

6.1 Models Output

[22]:
```
from prettytable import PrettyTable

table = PrettyTable()

table.field_names = ['Model', 'Vectorizer', 'Hyperparameter', 'Log Loss']

table.add_row(['Logistic Regression', 'TFIDF', 1e-05, 0.4140181065549573])
table.add_row(['Linear SVM', 'TFIDF', 1e-05, 0.44965497921483527])
table.add_row(['Logistic Regression', 'TFIDFW2V', 1e-05, 0.4140181065549573])
table.add_row(['Linear SVM', 'TFIDFW2V', 1e-05, 0.44965497921483527])
table.add_row(['Xgboost', 'TFIDFW2V', 1e-05, 0.4140181065549573])
table.add_row(['Xgboost with best hyperparameter', 'TFIDFW2V', 'n_estimators:
 ↪2000, max_depth:7', 0.3384723600838287])

print(table)
```

```
+----------------------------------+------------+-------------------------------
-+---------------------+
|              Model               | Vectorizer |         Hyperparameter
|       Log Loss      |
+----------------------------------+------------+-------------------------------
-+---------------------+
|       Logistic Regression        |   TFIDF    |             1e-05
|  0.4140181065549573 |
|            Linear SVM            |   TFIDF    |             1e-05
| 0.44965497921483527 |
|       Logistic Regression        |  TFIDFW2V  |             1e-05
|  0.4140181065549573 |
|            Linear SVM            |  TFIDFW2V  |             1e-05
| 0.44965497921483527 |
|             Xgboost              |  TFIDFW2V  |             1e-05
|  0.4140181065549573 |
| Xgboost with best hyperparameter |  TFIDFW2V  | n_estimators:2000, max_depth:7
|  0.3384723600838287 |
+----------------------------------+------------+-------------------------------
-+---------------------+
```

6.2 Steps I followed

- EDA on the data
- Pick 100K data points, split train and test then create TFID vectors of questions and run following ML Models on that:
  - Logistic Regression
  - Linear SVM

- Pick 100K data points, split train and test then create TFIDFW2V vectors of questions and run following ML Models on that:
  - Logistic Regression
  - Linear SVM
  - Xgboost
  - Xgboost with best Hyperparameter

6.3 Best Model

- Xgboost (TFIDFW2V) with best Hyperparameter gives log loss 0.3384723600838287

[ ]:
```
```